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ESSAYS ON EMPIRICAL ASSET PRICING IN SAUDI ARABIA

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ABSTRACT

The purpose of this dissertation is to investigate the determinants of expected returns in Saudi Stock Markets. In the first manuscript, we examine how lottery-like stocks are valued in Saudi Arabia where stock trades are dominated by Muslim individuals who have never experienced gambles/ lotteries. We find significant underperformance of lottery-like stocks in Saudi Arabia, especially among those with high stock turnover. We discuss a few channels through which investors in Saudi Arabia overpay for lottery-like characteristics despite their strong moral oppositions to gambles/lotteries.

The second manuscript aims to shed new lights into the factors that drive the cross-sectional variation of stock returns in Saudi stock market. This manuscript adds to the existing research in the following three ways. First, we show that stocks with lottery-like payoffs, as measured by the maximum daily return over the past one month (MAX), draw strong attention from retail investors as measured by an increased investor base and increased liquidity, after controlling for Islamic classification. MAX and the Islamic classification capture different aspects of investors' attention/ recognition. MAX effect thus complements the effect of Shariah compliance by drawing transitory attention of retail investors. Second, we document the presence of significant profitability effect in the cross-section of average returns in Saudi stock market. Third, we show that the significant profitability effect in Saudi stock market is concentrated in a group of firms with high maximum daily returns (MAX) over the past month, i.e., those with lottery-like features. The Islamic

classification, however, does not exhibit this moderating effect on the profitability effect in stock returns.

The third manuscript examines whether Islamic classification and MAX, defined as the maximum daily return over the past one month, exhibit a higher future crash risk in Saudi Stock Market. Saudi Stock Market was chosen because of some of its unique characteristics, such as the nature of its investors and the prevalence of Islamic investment models, and due to the importance of Islamic classification and MAX in this market, both which make it worth examining. The evidence shows that MAX is negatively associated with future crash risk after controlling for other predictors of crash risk. In contrast, the relation between Islamic classification and future stock price crash risk is weak.

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Manuscript 1

The Lottery-like Stocks Characteristics in Saudi Arabia

by

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Manuscript 1

The Lottery-like Stocks Characteristics in Saudi Arabia

Abstract

Existing studies suggest that stocks with lottery-like characteristics tend to underperform, especially when they attract retail trades, and that the degree of underperformance is closely related to investors' forgiving (vs. forbidding) attitude toward gambles/lotteries embedded in their religious norms. We examine how lottery-like stocks are valued in Saudi Arabia where stock trades are dominated by Muslim individuals who have never experienced gam- bles/lotteries. We find significant underperformance of lottery-like stocks in Saudi Arabia, especially among those with high stock turnover. We discuss a few channels through which investors in Saudi Arabia overpay for lottery-like characteristics despite their strong moral oppositions to gambles/lotteries.

1 Introduction

In making risky investment decisions, people often overweight small probabilities of large gains and underweight large probabilities of small gains ([16] [24] and [6]). This bias (probability weight- ing) leads to a preference for assets with lottery-like payoffs, i.e., small chances of extreme gains. It is then natural to suspect that such lottery-preferences may derive the well-documented overvalua- tion and return underperformance (negative return premiums) of lottery-like stocks. For example, [17] shows that the underperformance of lottery-like stocks is closely linked to investors' propensity to gamble, as actual lotteries and lottery-like stocks attract very similar socioeconomic clienteles. This study aims to address an interesting extension of [17] study by focusing on stock markets in Saudi Arabia that have never experienced gambles /lotteries. As noted by [3], domestic retail investors dominate 90% of trades in Saudi stock markets (Tadawul), while foreign institutional in- vestors have relatively limited access to Saudi stocks. Domestic investors are Muslims who adhere to the teaching of Islam (Shariah-principles), which strictly forbids gambles /lotteries and interest- bearing instruments. Saudi investors clearly represent a unique clientele who has been outside the consideration of many existing studies, and provides an interesting niche that needs to be filled. This study examines how lottery-like characteristics are priced in Saudi Arabia where there are no lotteries or gambles. Using the two standard measures of a stock's lottery-like characteris- tics—the maximum daily return over the prior month (MAX) and idiosyncratic return volatility (IVOL)— we find significant negative return premiums for MAX and IVOL in Saudi Arabia in the 2006-2018 period. Specifically, MAX and IVOL predict subsequent stock returns negatively and significantly in Fama-MacBeth cross-sectional regressions beyond the effects of market beta, size, book-to-market ratio, momentum, illiquidity, and oil price beta. The negative return premiums of IVOL are more pronounced among the subsample of firms with high stock turnover. These finding in Saud Arabia are generally consistent with those of [1], [2], [5], [13] among others. However, the significant under-performance of lottery-like stocks in Saudi Arabia was somewhat unexpected. To see why we did not expect significant underperformance of lottery stocks in Saudi Arabia, let us put our evidence in the context of the recent literature, which emphasize the effects of religious norms on individuals' lottery-preferences. For example, using a US sample, [18] show that the overvaluation of lottery-like stocks is larger in regions with high concentrations of Catholics relative to Protestants. They argue that the overvaluation of lottery-like stocks is related to the forgiving attitude toward gambles embedded in the investors' religious beliefs, as gambling is forbidden in Protestantism but not in Catholicism. [4] examine a sample of 45 countries and find significant underperformance of lottery-like stocks only in 11 countries that have more gambling activities and/or larger proportions of Catholics relative to Protestants. These results suggest that investors' attitudes toward gambles/lotteries, embedded in their religious norms, determine whether lottery-like stocks are overpriced or not. From a different angle, [19] document that countries with high religiosity have lower levels of venture capital investments that have lottery- like payoffs than those with low religiosity. They attribute the evidence to the findings of other studies that more religious people are inherently more risk-averse than less religious people ([14]; [8]). Saudi Arabia is among the most religious countries in the world by the religiosity measure used in [19]. Muslim investors in Saudi Arabia have strong moral oppositions to gambles /lotteries.

Following the evidence and interpretation of [18], [4] and [19], we would expect that the over- valuation of lottery-like stocks should be small or insignificant in Saudi stock markets. On the contrary, our evidence suggests that investors in Saudi stock markets tend to overpay for stocks with lottery-like characteristics. On appearance, the evidence looks inconsistent with the existing research, but it provides a few implications and research opportunities. First, religious Muslims in Saudi Arabia may not be as risk-averse as existing studies suggest. Many existing studies that associate religious beliefs with risk-aversion ([14]; [8]) do not consider Muslims in their investigations. There clearly exists a gap that needs to be filled with further research. Second, for Saudi Muslim investors, lottery-like stocks may be completely different from gambles /lotteries because these stocks represent real investment opportunities. They may prefer investing in lottery-like stocks as long as they comply with the main Shariah principles. Third, the overvaluation of lottery-like stocks in Saudi Arabia may be driven by forces other than investors' biases (probability weighting) and/or lottery preferences.

For example, a stock's recent extreme positive returns may draw retail investors' attention, and hence may increase the dispersion of opinions about its fundamental value. Because short-selling is strictly prohibited in Saudi Arabia, the stock is likely to be overvalued as the price will be set by the most optimistic investors. The classic paper by [21] originally suggested this mechanism, and [22] elaborate on this idea to explain the low-volatility puzzle. Fourth, the negative return premiums of lottery-like stocks may reflect positive return premiums on non-lottery-like stocks, i.e., stocks with low MAX and/or low IVOL. Although [21] and [22] focus on the overvaluation of lottery-like stocks in the presence of short-sale constrains, some non-lottery-like stocks may get undervalued because they do not attract investors' attention. We cannot rule out this as a possible explanation because negative return premiums of lottery-like stocks in Saudi Arabia are more pronounced among the stocks with high book-to-market ratios than among those with low book-to-market ratios. This result is opposite from the prediction of [22]. The third and fourth explanations are different from the original motivations for this study but warrant further investigations. These explanations rely on the view that a stock's lottery-like characteristics, such as extreme positive returns, draw investors' attention to the stock. We are currently examining the validity of these explanations in a follow-up study. The paper is organized as follows. Section 2 describes the data sources and methodology. Section 3 presents the main results. We conclude in Section 4 with a brief summary.

2 Data and Methodology

The data is daily stock prices of Saudi companies and their financial statements for the periods 2006-2018. The data is available on Tadawul's website. The monthly treasury bill rates data is obtained from Kenneth R. French for the period 2004-2018. There were 171 listed companies in the Saudi stock market by the end of the year 2015. However, after excluding firms with missing stock prices and some items of financial statements data, the number of companies in our sample is 140 companies. We use different measures for portfolio analysis. Following previous literature, variance of daily returns is estimated using 60 days of lagged returns. The return skewness of individual stocks is calculated using trailing 60 daily returns. Momentum is the stock return for the past 11 months, excluding the most recent month. The computation of market to book ratio is the current stock price of the outstanding shares divided by the book value of shares. In addition, we form different portfolios of Saudi stocks. We classify firms by size, big and small. we consider top half and bottom half as threshold, so we use the median to separate between big and small firms every month. We use the same approach to classify firms big small and high low for variance, skewness, momentum, and market to book ratio. We calculate illiquidity using Amihud's measure, which is the time-series average of absolute daily return divided by daily volume. To consider nonsynchronous trading, we follow [20], [9], and [23], and we use the lag and lead of the market portfolio as well as the current market when estimating market beta β

$$R_{i,d}-r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d-1}-r_{f,d-1}) + \beta_{2,i}(R_{m,d}-r_{f,d}) + \beta_{3,i}(R_{m,d+1}-r_{f,d+1}) + \varepsilon_{i,d} \quad (1)$$

where $R_{i,d}$ is the return on stock i on day d, $R_{m,d}$ is the market return on day d, and $r_{f,d}$ is the risk-free rate on day d. We estimate this equation for each stock using daily return within a month. The market beta of stock i in month t is defined as

$$\hat{\beta}_i = \hat{\beta}_{1,i} + \hat{\beta}_{2,i} + \hat{\beta}_{3,i} \quad (2)$$

3 Results

3.1 Variance Effect on Portfolio performance

In this section, we investigate whether there is a relation between stock returns and variance. We estimate idiosyncratic volatility as the variance of the residuals from regressing stock i daily excess returns using [11] three-factor as follow:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t} MKT + s_{i,t} SMB + \mathrm{h}_{i,t} HML + \varepsilon_{i,t} \quad (3)$$

The variance of the residuals εi,t is estimated using trailing 60 daily residual of Fama and French three factor model. We followed [12] and construct size (SMB) and value (HML). Big stocks are those in the top 50% of the market cap, while small firms are those in the bottom 50% of the market capitalization. The same approach is used for stocks with high and low market-to- book ratios. Then, we formed different portfolios sorted by variance, and this is for both equally weighted and value weighted. We form four portfolios:

(1) firms with highest idiosyncratic variance, (2) firms with high idiosyncratic variance, (3) firms with low idiosyncratic variance, and (4) firms with lowest idiosyncratic variance. Table 2 shows descriptive statistics of idiosyncratic volatility (IVOL) of all Saudi firms from 2007 to 2018. The number of listed firms increase gradually due to IPOs. IVOL seems persistent throughout the entire sample period. Although the maximum variance in 2011and 2012 is higher compared to the mean, they are considered outliers in this period. Table 4 reports the monthly average return and standard deviation of the low, middle, and high idiosyncratic volatility portfolios as well as t-statistic of the difference in means of low and high portfolio. We find a monotonic relation, and the significance of the difference in the average monthly returns between the low and high portfolios is big enough. There is a monotonic decrease in the average monthly return as we move from portfolios with low IVOL portfolio to portfolios with high IVOL. The average monthly return on high-idiosyncratic volatility portfolios is the lowest average monthly returns among the other portfolios, with 0.31% (EW) and 0.24% (VW) per month i, while the average monthly return on high-idiosyncratic volatility portfolio is 0.66% per month. We also do a two-step [10] regression analysis of the relation between variance and stock returns for value-weighted portfolios. Each month, we run a cross-sectional regression of stock return on one-month-lagged variance and other control variables. In the second step, we do the time-series averages of the monthly cross-sectional regression coefficients. In the univariate regressions in table 6, the coefficients on idiosyncratic volatility are negative

and statistically significant. The negative relation between stock returns and idiosyncratic volatility is even stronger after controlling for market beta, size, and book-to-market ratio. The low variance anomaly, that is low-variance stocks have higher returns than high-variance stocks, appears to be present in Saudi markets after controlling for the size, book-to-market, and illiquidity effects. The results hold even without the control of the aforementioned effects. As a robustness check, we rerun Fama–MacBeth regressions using total volatility instead of idiosyncratic volatility. Following previous literatures (e.g., [15]), total volatility is estimated using daily log returns over the past 60 days. We re-run Fama–MacBeth regressions of monthly returns on total volatility (TVOL) and aforementioned control variables for both equally-weighted and value-weighted portfolios. Table 6 shows a significant negative relation between stock returns and TVOL. The coefficients on TVOL across all model specifications (4,5, and 6) is negative and statistically significant. This indicates that variance effects exist in Saudi Stock Market even after controlling for size, book-to-market, and illiquidity effects. In other words, stocks with high variance tend to be overvalued in Saudi Arabia.

3.2 Variance Effect Sorted by Market-to-Book Ratio

We want to see if there are differences in variance effects between high market-to-book stocks and low market-to-book stocks. [22] find that the relation between implied volatility and average return is negative among overpriced stocks but positive among underpriced stocks. We formed different portfolios sorted by market-to-book ratio and variance. We form six portfolios: (1) stocks with high IVOL and high M/B ratio, (2) stocks with middle IVOL and high M/B ratio, (3) stocks with low IVOL and high M/B ratio, (4) stocks with high IVOL and low M/B ratio, (5) stocks with middle IVOL and low M/B ratio, (6) stocks with low IVOL and low M/B ratio. Table 9 reports the average monthly return and standard deviation of the low, middle, and high idiosyncratic volatility portfolios sorted by market to book as well as t-statistic of the difference in means of low and high portfolio. Among low market-to-book stocks, we find a monotonic relation, and the difference in the average monthly returns between low and high idiosyncratic volatility portfolios is pronounced. There is a monotonic decrease in the average monthly return as we move from portfolios with low variance to portfolios with high variance. The average monthly return on low-idiosyncratic volatility portfolio is the highest returns among the other portfolios in the same set, with 0.27% per month, while the monthly average return on high-idiosyncratic volatility portfolio is 0.98% per month. In contrast, it is hard to find a monotonic relation between average monthly returns and idiosyncratic volatility among stocks with high market-to-book ratio. It appears that stocks with high volatility and low market-to-book (high book-to-market) have low subsequent average monthly returns. We run a two-step [10] regressions of stock returns on IVOL sorted by book-to-market ratio (high, medium, and low) for both equally-weighted and value-weighted portfolios. Each month, we run a cross-sectional regression of stock return on one-month-lagged variance and other control variables. In the second step, we do the time-series averages of the monthly cross-sectional regression coefficients. Table 10 reports the results of Fama MacBeth regressions for only stocks with low market-to-book ratio. In all models (1-4) show a significant negative (at 1% level) relation between stock returns and IVOL. The negative relation between stock returns and IVOL is strong for equally-weighted portfolio even after controlling for size, illiquidity, beta of oil returns, and book-to-market effects. The coefficient on IVOL in model 4 is negative and statistically significant at 1% level. The significant negative relation between stock returns and IVOL appears to be present among stocks with low market-to-book ratio. In contrast, the negative relation between stock returns and IVOL seems to be disappeared among stocks with high market-to-book ratio. Table 11 shows the results of Fama MacBeth regressions for only stocks with high market-to-book ratio. Both the univariate and multivariate regressions exhibit no relations between stock returns and IVOL among stocks with high market-to-book ratio. These results shown in table 11 are consistent with the previous results introduced in table 9. The low variance effect is observed among the value stocks (low market-to-book or high book-to-market). From the aforementioned analysis, it appears that stocks with high variance and low market-to- book stocks are not cheap enough as they have low subsequent returns. In other words, high variance and low market-to-book stocks tend to be overvalued.

3.3 MAX Effects

The maximum daily return (MAX) within a month is also used as a proxy for lottery-like payoffs. Bali et al. (2011) use the maximum daily return in a month as a proxy for lottery-like features, and they investigate whether the extreme positive returns are significant in the cross-sectional pricing of stocks. They find that the maximum daily return in a month is negatively related to future returns. Investors might overpay for stocks that exhibited extreme positive returns in the past, expecting that this pattern will be repeated in the future. Following [23], we construct Maximum that is the maximum daily return within a month:

$$\mathrm{MAX}_{i,t} = \max\left(R_{i,d}\right), \quad d = 1, \ldots, D_t, \tag{4}$$

Where $R_{i,d}$ is the return on stock *i* on day d and D_t is the number of trading days in month *t*. We want to examine the persistence of MAX. If MAX is totally random, it should say nothing about the maximum daily return in the following month. We also run a two-step Fama MacBeth regressions of maximum daily return within that month on the maximum daily return from previous month and other lagged control variables that are market beta, size, book-to-market (B/M), momentum (MOM), Illiquidity measure (ILLIQ), and idiosyncratic variance (IVOL). The definitions of these control variables are mentioned earlier. Table 5 reports the average cross- sectional coefficients and standard errors from these regressions. In the univariate regression, model 1, the coefficient on lagged MAX is positive and statistically significant, and the

R-square is 8.4%, indicting substantial cross-sectional explanatory power. When we include the control variables, the coefficient on lagged MAX is positive and statistically significant. IVOL and size contribute significantly to the explanatory power of the regression with univariate R-squareds of 12.9% and 8%, respectively. The other control variables all have univariate R-squareds of less than 5%. The results shown in table 5 indicates that stocks that have extreme positive daily returns in one month tend to have similar features in the following month. After we confirm the persistence of MAX, we now examine the cross-sectional relation between MAX and expected stock returns using the following model:

$$\begin{aligned} R_{i,t+1} \quad = \quad & \lambda_{0,t} + \lambda_{1,t} MAX_{i,t} +_{2,t} BETA_{i,t} + \lambda_{3,t} SIZE_{i,t} + \lambda_{4,t} BM_{i,t} \\ & + \lambda_{5,t} MOM_{i,t} + \lambda_{6,t} ILLIQ_{i,t} + \lambda_{7,t} IVOL_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{5}$$

Where $R_{i,t+1}$ is the realized stock return on stock i in month $t + 1$. BETA is the market beta. The remaining variables are defined earlier. We run the monthly cross-sectional regressions on the one- month lagged values of MAX, market beta, size, B/M, momentum, illiquidity, and idiosyncratic variance. Table 6 shows the results of [10] regressions using the aforementioned model. In the univariate regression, model 4, the coefficient on MAX is negative and statistically significant at 5% level, indicating a negative relation between the maximum daily returns and the future stock returns. The time-series average of the slope coefficient is -0.23, with a t-statistic of -2.30. The time-series average of the slope coefficient on MAX across all model specifications are negative and significant at 5% or 1% level. In the multivariate regression, model 8, the coefficient on MAX is negative and statistically significant even after controlling for B/M, size, and the other effects. The average slope coefficient is -0.238 with a t-statistics of 2.80. These results provide an evidence that suggests that investors in Saudi Arabia overvalue stocks that exhibit extreme positive returns, and therefore, these stocks exhibit lower returns in the future. This is consistent with cumulative prospect theory developed by [24], which is modeled in [7]. Investors make errors in weighing the probability, which cause them to pay more for stocks that have a small probability of a large positive return.

3.4 Speculative Retail Trading

It is documented that lottery-like stocks attract retail investors, and thus, they pay more for stocks that exhibit these features. [13] that stocks with high retail trading proportion (RTP) exhibit strong lottery characteristics, and they attract retail investors with strong gambling propensity, and these stocks tend to be overpriced. Given that fact that 90 percent of Saudi stocks are traded by retail investors and the motivation by [13] and other earlier studies, we investigate the extent to which retail investors in Saudi Arabia overpay lottery-like stocks. In other words. we want to investigate whether stocks with lottery-like features are held and actively traded by retail investors. [13] use small trades (trade size below $5, 000) as a proxy for retail trades, and then they divide that by the total trading volume in the same month. In Saudi Stock Market, there is no need to use a proxy to identify retail trades since 90% of daily trades in Saudi stock market is done by retail investor, according to Saudi Stock Exchange (Tadawul). Therefore, we directly use stock turnover, which is calculated as the ratio of traded stock volume over firm total shares outstanding We want to examine the stock preferences of individual investors more accurately. Following [13], we run [10] regressions of a stock's RTP on several stock characteristics including lottery-like features. Table 7 reports the [10] regression estimates where the dependent variable is retail trading volume. The results in model 1 show a significant positive relation between speculative trading activities of retail investors and IVOL, meaning that retail investors are more active in trading stocks with high idiosyncratic variance. Also, the results show significant negative coefficients on both stock price and dividend-paying dummy, indicating that retail investors trade low-priced stocks and non-dividend-paying status more actively. The coefficients on idiosyncratic variance, stock price, and dividend-paying dummy are still significant even after adding other control variables. The results hold for both equally-weighted and value-weighted portfolios. We can see from these results that retail investors are very active in trading lottery-like stocks, and even more they overpay such stocks, which is completely consistent with [13]. We now investigate whether we observe variance effects among turnover groups. We run a two-step [10] regressions of stock returns on IVOL and other control variables sorted by stock turnover. Each month, we run a cross-sectional regression of stock return on one-month-lagged variance and other control variables. In the second step, we do the time-series averages of the monthly cross-sectional regression coefficients. We sort the portfolios into three groups based on turnover, lowest-turnover portfolio, middle-turnover portfolio, and highest-turnover portfolio. The third column in table 8, lowest-turnover portfolio, show negative but not strongly significant. As we move from lowest-turnover portfolio to highest- turnover portfolio, the magnitude of the coefficient on IVOL becomes larger and more significant. In the last column, the coefficient on IVOL is negative and statistically significant at 1% level. The results exhibit strong negative variance effect among stocks with the high turnover, and this is consistent with what we observe in the U.S. This suggests that retail investors in Saudi Arabia pay more for lottery-like stocks.

4 Conclusion

We use Saudi stock market, where 90 percent of its stocks are traded by retail investors who have not been exposed to gambling, to examine whether stocks with lottery-like features are overvalued. We find that lottery-like stocks as those with high idiosyncratic volatility and extreme positive returns underperform. Moreover, we find that high volatility and low market-to-book stocks tend to be overvalued. We also find strong negative variance effects among stocks with high turnover. Our results suggest that Saudi retail investors, despite their moral opposition to lotteries and gambles, tend to overpay for stocks with lottery-like characteristics. This evidence is a very interesting contribution to the literature which has shown that the overvaluation (negative return premiums) of lottery-like stocks are closely related to cultural attitudes toward gambles.

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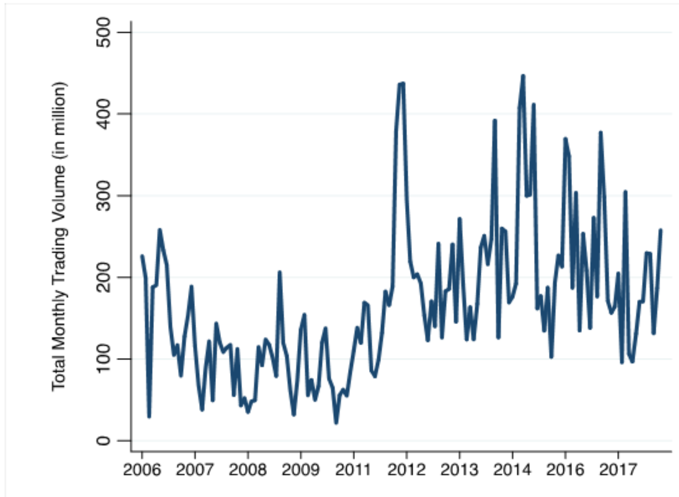

Figure 1: Total Monthly Trading Volume

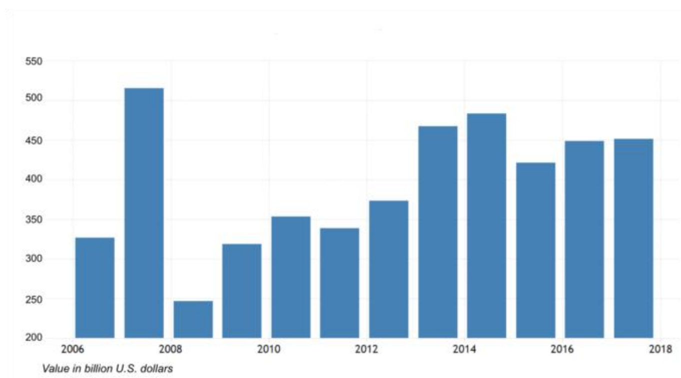

Figure 2: Total Market capitalization of Saudi stock market

Table 1: Descriptive Statistics of The Returns of All Firms

Year	N of Firms	Mean	SD	Min	p5	p25	p50	p75	p95	Max
2006	44	-3.17	29.67	-62.00	-45.75	-22.38	-3.75	10.82	47.92	204.76
2007	59	3.09	12.77	-34.34	-16.86	-4.41	2.44	10.26	25.00	75.47
2008	69	-5.83	14.92	-60.83	-30.30	-13.96	-5.15	1.98	16.67	94.23
2009	77	3.36	12.88	-24.51	-12.75	-4.05	1.36	8.02	26.82	105.14
2010	85	0.15	7.71	-25.71	-12.41	-3.99	0.00	4.61	12.54	60.64
2011	123	1.95	10.73	-46.88	-11.80	-4.62	0.54	7.11	17.95	91.42
2012	128	1.94	13.91	-47.91	-14.38	-5.41	0.89	7.38	20.90	234.08
2013	136	1.96	8.65	-59.49	-9.48	-2.33	1.24	5.66	15.02	117.19
2014	138	0.21	10.69	-48.92	-17.52	-5.72	0.34	6.19	16.41	68.92
2015	140	-0.98	11.55	-54.19	-20.12	-6.89	-0.96	4.58	17.08	109.81
2016	139	0.72	13.94	-53.21	-21.25	-6.97	0.15	8.16	23.69	127.14
2017	140	0.00	8.67	-44.76	-10.90	-4.51	-0.60	3.40	12.84	150.29
2018	140	0.75	7.41	-33.82	-8.11	-3.18	-0.25	3.08	13.33	73.63
Total		0.51	12.59	-62.00	-17.67	-5.38	0.00	5.88	19.00	234.08

Note: Table 1 reports the mean stock returns of 140 firms listed in Saudi Stock Exchange (Tadawul). N of Firms represents the unique number of firms in the sample by period. Mean is the mean of the monthly average return of the individual stocks and represented as a percentage (e.g. total = 12.98 %). Adjusted Closing Price for Dividends is used to compute the monthly average return of stocks. The sample is for the period 2006-2018. SD is the standard deviation.

Table 2: Descriptive Statistics of The Idiosyncratic Volatility of All Firms

Year	N of Firms	Mean	SD	Min	p5	p25	p50	p75	p95	Max
2007	59	10.19	4.05	3.85	5.13	7.38	9.59	12.06	16.72	32.23
2008	69	13.08	3.72	3.69	7.50	10.53	12.73	15.38	19.61	26.03
2009	77	11.98	4.69	3.09	5.33	8.30	11.25	15.01	20.75	24.36
2010	85	7.32	2.25	2.21	3.81	5.67	7.12	8.91	10.92	16.30
2011	123	7.99	4.72	2.25	3.99	5.45	7.07	9.38	14.26	68.01
2012	128	8.59	4.64	1.88	3.84	5.72	7.52	10.52	15.25	67.99
2013	136	7.06	3.33	1.72	3.41	5.07	6.42	8.20	12.23	38.11
2014	138	7.75	3.24	1.74	3.68	5.53	7.20	9.12	14.29	22.51
2015	140	10.10	3.08	2.37	5.18	7.96	9.90	12.07	15.13	25.54
2016	139	10.23	3.71	2.64	5.25	7.74	9.75	12.06	16.61	33.62
2017	140	7.81	3.06	0.14	4.23	5.77	7.29	9.19	13.60	28.94
2018	140	7.95	3.24	0.19	4.62	5.91	7.23	9.32	12.62	29.47
Total		8.95	4.06	0.14	4.11	6.13	8.22	10.92	16.06	68.01

Note: This table reports the mean idiosyncratic volatility of firms listed in Saudi Stock Exchange (Tadawul). N of Firms represents the unique number of firms in the sample by period. Mean is the mean of the average monthly return variances of the individual stocks. The idiosyncratic variances of the individual stocks are calculated using trailing 60 daily residual of Fama and French three factor model. SD is the standard deviation.

Table 3: Descriptive Statistics of RTV of All Firms

Year	N of Firms	Mean	SD	Min	p5	p25	p50	p75	p95	Max
2006	44	3,630,444	4,432,561	900	98,310	829,448	2,252,513	4,670,941	13,000,000	28,200,000
2007	59	1,967,188	2,651,220	8,379	68,129	376,350	1,090,043	2,478,024	7,036,427	26,700,000
2008	69	1,135,078	1,930,784	6,233	51,860	214,246	535,364	1,185,345	4,332,382	25,000,000
2009	77	1,284,845	3,531,192	2,070	36,280	174,474	517,974	1,306,755	4,305,878	86,300,000
2010	85	784,893	2,075,213	737	19,994	97,370	250,841	676,568	3,151,944	35,100,000
2011	123	1,203,262	2,085,018	2,102	37,153	154,890	487,260	1,296,991	4,898,530	21,400,000
2012	128	1,768,978	5,521,784	9,434	41,199	176,484	477,107	1,360,439	6,096,922	121,000,000
2013	136	1,224,812	3,584,448	4,110	47,115	176,211	424,692	955,566	3,700,485	47,700,000
2014	138	1,611,940	4,775,323	8,414	68,036	225,247	540,415	1,327,313	5,168,556	81,500,000
2015	140	1,541,869	5,818,463	1,806	35,136	157,194	392,679	989,867	4,740,309	127,000,000
2016	139	1,655,489	6,414,963	1,125	35,312	189,365	459,121	1,096,087	4,756,284	105,000,000
2017	140	1,087,838	4,766,687	1,395	21,681	83,309	203,697	565,151	3,218,796	80,500,000
2018	140	1,300,433	5,320,261	2,367	28,071	114,912	257,454	638,838	3,795,354	80,900,000
Total		1,465,415	4,603,717	737	36,165	157,950	436,545	1,170,740	5,098,700	127,000,000

Note: This table reports descriptive statistics of the retail trading volume (RTV). According to Tadawul, RTV is 90% of the total trading volume. N of Firms represents the unique number of firms in the sample by period. Mean is the mean of the monthly volume traded. SD is the standard deviation.

Table 4: Means for Different Portfolios

IVOL	Low (1)	Middle (2)	High (3)	Difference (1) - (3)
Mean	0.65	0.74	0.24	0.41
Standard Deviation	6.32	8.08	8.31	5.32
t - test				0.85
MAX				
Mean	0.61	-0.08	-0.31	0.92
Standard Deviation	7.96	9.42	9.77	6.13
t - test				1.81

Notes: This table represents the average monthly return, standard deviation of the low, middle, and high value-weighted portfolios for idiosyncratic volatility and MAX as well as t-statistic of the difference in means of low and high portfolios. Idiosyncratic volatility of the individual stocks is calculated using trailing 60 daily residual of Fama and French three factor model. It is the maximum daily return over the past one month.

Table 5: Cross-Sectional Predictability of MAX

	Dependent Variable = MAX							
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged Max	0.24							0.11
	(12.63)							(4.44)
Mkt Beta		0.37						0.075
		(3.19)						(1.59)
Size			-0.17					-0.13
			(-0.97)					(-5.15)
B/M				-0.46				-0.32
				(-5.70)				(-4.21)
MOM					0.08			-0.04
					(0.43)			(-0.27)
ILLIQ						-9.99		-9.62
						(-1.33)		(-1.90)
IVOL							1.00	0.79
							(5.14)	(9.65)
R-squared	0.08	0.04	0.08	0.05	0.04	0.02	0.13	0.25

Note: This table reports Fama–MacBeth regressions of the maximum daily in that month (MAX) each month on subsets of lagged predictor variables. Mkt beta is market beta calculated using the lag and lead of the market portfolio as well as the current market when estimating market beta. Size is the lagged log of market chaptalization of the individual stocks calculated by multiplying the share price by the number of shares outstanding. B/M is the lagged log of book to price ratio. Mom is momentum, which is the stock return for the past 11 months excluding the most recent month. ILLIQ is illiquidity calculated using Amihud's measure, which is the time-series average of absolute daily return divided by daily volume. IVOL is idiosyncratic variance, and it is estimated using trailing 60 daily residual of Fama and French three factor model. t-statistics are shown in parentheses.

Table 6: Fama–MacBeth Regressions - Idiosyncratic Volatility, MAX, and Total Volatility

	Dependent Variable = Return								
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IVOL	-0.14	-0.16	-0.15						
	(-1.78)	(-1.68)	(-1.85)						
MAX				-0.23	-0.14	-0.24			
				(-2.30)	(-1.69)	(-2.81)			
TVOL							-0.05	-0.11	-0.10
							(-0.94)	(-1.75)	(-1.68)
Mkt Beta		-0.49	-0.38		-0.19	-0.04		-0.44	-0.23
		(-1.48)	(-1.27)		(-0.67)	(-0.13)		(-1.22)	(-0.67)
Size		-0.05	-0.18		0.02	-0.16		-0.05	-0.17
		(-0.39)	(-1.37)		(0.15)	(-1.37)		(-0.44)	(-1.27)
MOM		0.37	0.36		-0.04	-0.21		0.66	0.10
		(0.48)	(0.43)		(-0.06)	(-0.22)		(0.82)	(0.10)
B/M			-0.70			-0.86			-0.93
			(-2.19)			(-2.63)			(-2.94)
ILLIQ			-49.65			-59.87			-39.34
			(-2.63)			(-2.30)			(-1.16)
Oil Return Beta			-0.33			-0.42			-0.45
			(-0.45)			(-0.65)			(-0.65)
R-squared	0.08	0.25	0.36	0.06	0.25	0.37	0.10	0.28	0.39

Notes: This table reports Fama–MacBeth regressions of stock returns in each month on subsets of lagged one-month variables including control variables (value-weighted portfolio). The independent variables are the following: IVOL is lagged one-month idiosyncratic volatility, and it is estimated using trailing 60 daily residual of Fama and French three factor model. MAX is lagged one month, and it is the maximum daily return over the past one month. TVOL is lagged one-month total volatility, and it is estimated using daily log returns over the past 60 days. Mkt beta is market beta calculated using the lag and lead of the market portfolio as well as the current market when estimating market beta. Size is the lagged log of market chaptalization of the individual stocks calculated by multiplying the share price by the number of shares outstanding. B/M is the lagged log of book to price ratio. Mom is momentum, which is the stock return for the past 11 months excluding the most recent month. ILLIQ is illiquidity calculated using Amihud's measure, which is the time-series average of absolute daily return divided by daily volume. Oil Return beta is coefficient, obtained from monthly regressions of an individual stock return on oil return using a window of 24 months. The dependent variable is the monthly returns of the individual asset. Adjusted closing price for dividends is used to compute the average monthly return of stocks. t-statistics are shown in parentheses.

Table 7: Fama-MacBeth Regression Estimates - Retail Investors

	Dependent Variable = Retail Trading Volume		
Independent Variable	(1)	(2)	(3)
Intercept	15.06	11.95	4.62
	(119.23)	(66.25)	(24.86)
IVOL	0.08	0.13	0.03
	(10.60)	(16.98)	(6.18)
Skewness	-0.02	-0.08	-0.02
	(-0.76)	(-3.52)	(-1.16)
Stock Price	-0.70	-0.56	-0.22
	(-39.19)	(-25.91)	(-13.28)
Dividend-Paying Dummy	-0.48	-0.86	-0.34
	(-10.58)	(-23.23)	(-13.43)
M/B		-0.46	-0.17
		(-13.70)	(-6.12)
Size		0.33	0.12
		(31.18)	(10.73)
MOM		0.07	0.07
		(1.29)	(1.79)
Mkt Beta			0.05
			(2.56)
Lagged RTV			0.62
			(53.98)
R-squared	0.31	0.47	0.68

Note: This table reports Fama–MacBeth regressions of the retail trading volume (RTV) on subsets of lagged one-month variables including control variables. RTV is 90% of the total trading volume. Idiosyncratic variances of the individual stocks are calculated using trailing 60 daily residual of Fama and French three factor model. Idiosyncratic skewness is the lagged skewness, and it is estimated using trailing 60 daily residual of Fama and French three factor model. A dividend-paying dummy variable (set to 1 if the stock pays a dividend at least once during the previous year). M/B is the lagged log of price to book ratio. Size is the lagged log of market chaptalization of the individual stocks calculated by multiplying the share price by the number of shares outstanding. t-statistics are shown in parentheses.

Table 8: FMB Regressions - Idiosyncratic Variance Sorted by Turnover

	Dependent Variable = Return			
	Equally Weighted		Value Weighted	
Independent Variable	Low	High	Low	High
IVOL	-0.154	-0.37	-0.14	-0.33
	(-2.05)	(-3.42)	(-1.24)	(-2.58)
Mkt Beta	0.290	0.40	-0.12	0.17
	(0.89)	(0.74)	(-0.27)	(0.31)
Size	0.01	-0.08	-0.26	0.17
	(0.14)	(-0.20)	(-1.99)	(0.41)
MOM	1.16	-3.50	1.35	-2.42
	(1.28)	(-2.52)	(1.17)	(-1.68)
B/M	-0.94	-1.81	-0.78	-1.17
	(-3.49)	(-3.09)	(-2.01)	(-1.72)
ILLIQ	-29.03	-7.63	-49.05	-33.09
	(-1.64)	(-0.12)	(-2.41)	(-0.35)
Oil Return Beta	0.55	-0.80	0.25	-1.87
	(0.69)	(-0.72)	(0.25)	(-1.53)
R-squared	0.31	0.36	0.47	0.50

Notes: Stocks are grouped into tertiles grouping by stock turnover (low, middle, and high). Low represents stocks with low turnover, and high represents stocks with high turnover. The middle group is not reported. Turnover is calculated as the ratio of traded stock volume over firm total shares outstanding. The dependent variable is the monthly returns of the individual asset. The independent variables are the following: Idiosyncratic variance is the lagged variance, and it is estimated using trailing 60 daily residual of Fama and French three factor model. Size is the lagged log of market chaptalization of the individual stocks calculated by multiplying the share price by the number of shares outstanding. B/M is the lagged log of book to price ratio. ILLIQ is illiquidity calculated using Amihud's measure, which is the time-series average of absolute daily return divided by daily volume. Adjusted closing price for dividends is used to compute the average monthly return of stocks, and t-statistics are shown in parentheses.

Table 9: Means for Different Portfolios

Variance (Low M/B)	Low (1)	Middle (2)	High (3)	Difference (1) - (3)
Mean	0.27	-0.28	-0.98	1.25
Standard Deviation	5.85	8.43	7.38	5.62
t - test				2.24
Variance (High M/B)				
Mean	1.51	0.81	1.18	0.33
Standard Deviation	5.82	7.36	9.31	8.55
t - test				0.43

Notes: This table represents the average monthly return, standard deviation of low, middle, and high value-weighted portfolios for idiosyncratic variance as well as t-statistic of the difference in means of low and high portfolio. This table represents the results for two different samples; low market-to-book ratio and high market-to-book ratio. Low M/B stocks are those with a bottom 1/3 of M/B ratio while high M/B stocks are those with a top 1/3 of M/B ratio. Idiosyncratic variances of the individual stocks are calculated using trailing 60 daily residual of Fama and French three factor model.

Table 10: Fama–MacBeth Regressions - Idiosyncratic Variance (Low M/B)

	Dependent Variable = Return			
	Equally Weighted		Value Weighted	
Independent Variable	(1)	(2)	(3)	(4)
IVOL	-0.32	-0.28	-0.36	-0.27
	(-4.31)	(-3.82)	(-3.56)	(-2.16)
Mkt Beta	0.14	0.32	0.15	0.44
	(0.51)	(1.09)	(0.34)	(1.10)
Size	-0.23	-0.10	-0.26	-0.05
	(-1.41)	(-0.63)	(-1.35)	(-0.26)
MOM	-0.67	-0.39	0.11	-0.48
	(-0.82)	(-0.37)	(0.09)	(-0.32)
B/M		-0.40		-0.63
		(-0.70)		(-0.79)
ILLIQ		33.40		91.19
		(0.44)		(1.28)
Oil Return Beta		-0.26		-1.66
		(-0.20)		(-1.04)
R-squared	0.24	0.35	0.38	0.54

Notes: This table reports Fama–MacBeth regressions of stock returns in each month on subsets of lagged one-month variables including control variables. The sample contains only stocks with low market-to-book ratio. The independent variables are the following: IVOL is lagged one-month idiosyncratic volatility, and it is estimated using trailing 60 daily residual of Fama and French three factor model. Size is the lagged log of market chaptalization of the individual stocks calculated by multiplying the share price by the number of shares outstanding. B/M is the lagged log of book to price ratio. The dependent variable is the monthly returns of the individual asset. ILLIQ is illiquidity calculated using Amihud's measure, which is the time-series average of absolute daily return divided by daily volume. Oil Return beta is coefficient, obtained from monthly regressions of an individual stock return on oil return using a window of 24 months. Adjusted closing price for dividends is used to compute the average monthly return of stocks. t-statistics are shown in parentheses.

Table 11: Fama–MacBeth Regressions - Idiosyncratic Variance (High M/B)

	Dependent Variable = Return			
	Equally Weighted		Value Weighted	
Independent Variable	(1)	(2)	(3)	(4)
IVOL	-0.12	-0.14	-0.12	-0.16
	(-1.34)	(-1.72)	(-1.08)	(-1.51)
Mkt Beta	0.14	0.15	-0.93	-0.85
	(0.33)	(0.39)	(-1.83)	(-1.74)
Size	-0.22	-0.32	0.01	-0.16
	(-1.18)	(-1.50)	(0.04)	(-0.87)
MOM	-1.93	-1.68	-0.10	0.30
	(-2.09)	(-1.61)	(-0.11)	(0.27)
B/M		-0.08		-0.10
		(0.12)		(-0.15)
ILLIQ		-37.67		-31.81
		(-1.59)		(-1.14)
Oil Return Beta		0.60		-0.34
		(-0.73)		(-0.33)
R-squared	0.28	0.39	0.37	0.53

Notes: This table reports Fama–MacBeth regressions of stock returns in each month on subsets of lagged one-month variables including control variables. The sample contains only stocks with high market-to-book ratio. The independent variables are the following: Idiosyncratic variance is the lagged variance, and it is estimated using trailing 60 daily residual of Fama and French three factor model. Size is the lagged log of market chaptalization of the individual stocks calculated by multiplying the share price by the number of shares outstanding. B/M is the lagged log of book to price ratio. The dependent variable is the monthly returns of the individual asset. ILLIQ is illiquidity calculated using Amihud's measure, which is the time-series average of absolute daily return divided by daily volume. Oil Return beta is coefficient, obtained from monthly regressions of an individual stock return on oil return using a window of 24 months. Adjusted closing price for dividends is used to compute the average monthly return of stocks, and t-statistics are shown in parentheses.

Manuscript 2

What Factors Drive Saudi Stock Market?

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Manuscript 2

What Factors Drive Saudi Stock Market?

Abstract

Since the recent inclusion in the global equity market index, Saud stock market has drawn strong attention from international investors. However, relatively little has been documented about the uniqueness of Saudi stock market. This study shows that, a stock's lottery-like feature, as measured by the maximum daily return over the past month (MAX), is strongly associated with a short-term increase in its investor-base and liquidity, beyond the effect of Islamic classification. Firms with high operational profitability have significantly higher average returns than others, and this profitability effect is more pronounced among the stocks with high MAX. The evidence suggests that retail investors' short-term attentions have significant effects on the cross-section of Saudi stock returns.

1 Introduction

In August 2019, the Saudi Stock Exchange (Tadawul) and Morgan Stanley Capital International (MSCI) completed the inclusion of Saudi stock market into the MSCI Emerging Market Index. Saudi stock market accounted for 2.8% of the index's total market capitalization at that time, comparable to stock markets in Mexico or Thailand in total capitalization. The inclusion of Saudi stocks to the popular emerging market index has drawn strong interests in Saudi stock market that had been segregated from other world stock markets.1 As the rapid integration of world stock markets has made it more difficult to deliver the benefit of international diversification than before, global investors are increasingly interested in differentiated markets to enhance diversification benefits and in under- standing unique country-specific factors that drive stock returns in Saudi Ara- bia. However, only a few empirical studies have investigated the cross-section of Saudi stock returns. This study aims to shed new lights into the factors that drive the cross-sectional variation of stock returns in Saudi stock market by building upon the studies of [Merdad et al., 2015] and [Alhomaidi et al., 2019]. One of the distinguishing features of Saudi stock market is the dominance of religious retail investors. According to Tadawul, 90 percent of Saudi stocks are traded by individual Muslim investors (see also [Alhomaidi et al., 2019]). Religious

[1] Although Tadawul is the largest capital market in the Middle East and North Africa, the market had been segregated from other markets. In 2015, Tadawul opened limited access to Qualified Foreign Investors (QFIs) with at least US$5 billion in assets under management and with at least five years of experience. Since then, Saudi Arabia has introduced several reforms to entice foreign investors and issuers, but it still enforces restricted access on Tadawul. See https://cma.org.sa/en/Market/QFI/Documents/QFIF AQE N.pdf

and sociocultural norms have large effects on these individuals' investment decisions beyond pecuniary considerations. For example, many individuals pursue investment objectives that are consistent with the teachings of Islam (Shariah principles). [Merdad et al., 2015] and [Alhomaidi et al., 2019] show that stocks of Shariah-compliant firms (Islamic stocks) and non-Shariah-compliant stocks (conventional stocks) behave differently in Saudi stock market.[2] For instance, stocks exhibit stronger return co-movements within Islamic and conventional groups of stocks than between the two groups, and Islamic stocks tend to have lower average returns (or higher valuations) than conventional stocks ([Merdad et al., 2015]). Moreover, [Alhomaidi et al., 2019] show that the Islamic classification draws stronger investor recognition than conventional stocks as measured by a broader investor-base and higher liquidity. These well-recognized Islamic stocks in Saudi market exhibit greater integration with global markets than less-recognized conventional stocks. This study adds to the existing research in the following three ways. First, we show that stocks with lottery-like payoffs, as measured by the maximum daily return over the past one month ("MAX") by [Bali et al., 2011], draw strong attention from retail investors as measured by an increased investor base and increased liquidity. We use the MAX measure in particular because [Bali et al., 2011] and [Han and Kumar, 2013b] show that MAX attracts trades by under-diversified retail investors. On appearance, MAX and

[2] A few studies examine the effects of Islamic factors using international equity indexes. For example, [Safiullah and Shamsuddin, 2019] consider 42 Dow Jones Islamic and non- Islamic equity portfolios and show that Islamic portfolios tend to have lower exposures to [Fama and French, 2015] five factors and higher alphas than conventional (non-Islamic) counterparts.

the Islamic classification (Shariah- compliance) have similar effects on investor attention/recognition. However, MAX is a transitory (fast-moving) stock characteristic whereas the Islamic classification is a highly persistent (slowly-moving) firm characteristic. MAX and the Islamic classification capture different aspects of investors' attention/ recognition. MAX effect thus complements the effect of Shariah compliance by drawing transitory attention of retail investors. Second, we document the presence of significant profitability effect in the cross-section of average returns in Saudi stock market. In our sample of Saudi stocks between 2006 and 2018, stocks with high operational efficiency or profitability, as measured by the sales/book equity, operating profits/book equity, and the return on equity (ROE), exhibit significantly higher average stock returns than others in Saudi Arabia. Third, we show that the significant profitability effect in Saudi stock market is concentrated in a group of firms with high maximum daily returns (MAX) over the past month, i.e., those with lottery-like features. The Islamic classification, however, does not exhibit this moderating effect on the profitability effect in stock returns. In light of the presence of many limits to arbitrage in Saudi stock market,3 our evidence yields the following straightforward interpretation. Retail investors tend to pay attention to stocks with high maximum daily returns (MAX). These investors tend to bid up stock prices of the firms with high operating efficiency/profitability. To the extent that this effect of increased investor attention take place gradually rather than

[3] These limits include no-short-selling restrictions, no leverage, limited access by foreign institutions, etc.

immediately in the presence of limits to arbitrage, profitable stocks tend to outperform other stocks in the subsequent month. The significant moderating effect of MAX (a transitory lottery-like feature), rather than the persistent effect of Islamic classification, suggests that the profitability effect in Saudi stock market reflect retail investors' transitory behaviors, rather than the effects of systematic risk exposures associated with the stocks. To our knowledge, ours is the first to document the moderating effect of MAX on the profitability effect in Saudi stock market. Our results are important to global investors. International diversification has become more difficult, as global stock market have integrated together. Investors no longer have much diversification benefits even when they invest in foreign stocks. Global investors are thus looking for unique markets, and Saudi stock market is one of the attractive options. However, only a few empirical studies have been done on Saudi stock market. This study investigates the cross-section of Saudi stock returns to understand the unique risk involved in Saudi stock Market. The pa- per is organized as follows. Section 2 describes Saudi Arabia's economy, Saudi stock market, and answering the question that why we choose Saudi stock market. Section 3 is a literature review about gambling and what have been done in this area. Section 4 describes the data sources and methodology. Section 5 presents the empirical work and main results. We conclude in section 6 with a brief summary.

2 Saudi Arabia's Economy and The Stock Market

2.1 Saudi Arabia's Economy

The Saudi economy is one of the largest twenty economies in the world (G20). It is an oil-based economy. Saudi Arabia has the second largest proven petroleum reserves, which accounts for 20% of the world's proven reserves, and is a major player in OPEC. Saudi Arabia is the biggest exporter of petroleum in the world. In 2016, the government of Saudi Arabia launched 2030 Vision to reduce the country's dependency on oil and diversify its economic resources. The Saudi currency (SAR) has been officially pegged to the US dollar at USD1 = 3.75SAR since 1975.

Zakat is imposed at a flat rate of 2.5%, and it is chargeable on the total of the company's capital resources and earnings that are not invested in fixed assets. In addition, debts used to acquire to fixed assets, inventory, and investments are subject to Zakat, which means there is no tax advantages for debts. Islamic finance is an important matter to investors in Saudi Arabia. The Islamic financial products comply with Islamic rules and principles. Some of these rules are objective, and the others are subjective. For this reason, Islamic scholars have different opinions about some Shariah compliance criteria. There exist some Islamic principles or rules that all scholars agree upon even though there are different schools of scholars, who define different screening criteria.

Overall, we can classify Shariah screening procedures into qualitative screening and quantitative screening. Qualitative screening is to categorize the business activity of the company, and based on that firms will be classified as Shariah compliant or not. For example, a company will not be categorized as Shariah compliant if its income source from alcohol, tobacco, pork-related products, conventional financial services, weapons, or entertainment exceeds 5% of its total revenue because entertainment serve alcohol and other prohibited activities such as gambling. Quantitative screening is most debatable among Shariah scholars. After passing the qualitative screening, Islamic scholars screen the company's financial health with a focus on solvency-ratios to determine the degree of Shariah compliance of a firm. For example, some scholars state that if the company has conventional debts (Non-Islamic loans) exceeding the respective threshold 33.33% of its market capitalization, the company is classified as non-compliant and thus it has to be excluded from Shariah- compliant portfolios.

The firm's classification will impact its trading and liquidity in stock market through two paths, [Alhomaidi et al., 2019]. The first path is that Shariah classification creates a barrier by restricting investors who seek only Islamic financial products to invest only in Shariah compliant stocks. The second path is that Shariah classification actively promotes Shariah-compliant stocks by increasing the base of potential investors for such stocks, making them recognized by a greater number of investors than non-Shariah compliant firms.

The stock market of Saudi Arabia has unique characteristics. Retail investors are very active in Saudi stock market. Most of the traders in Saudi stock market are individuals. According to Saudi Stock Exchange (Tadawul), 90 percent of Saudi stocks are traded by retail investors.   In addition, the equity mar- ket in Saudi Arabia is dominated by Saudi retail investors. As documented by Tadawul, the foreign investors in Saudi stock market accounts for 2% of the total investors, whereas the ratio of foreign investors to the total investors in markets of other Muslim countries is much larger than this ratio Therefore, Saudi equity market is very pure in terms of demographic characteristics. Moreover, there is no dual listing in Saudi market. All Saudi public companies are traded only in Saudi Arabia, so they do not use dual listing. This makes the market even purer in terms of geographic and demographic characteristics. Also, in terms of financial markets, Saudi equity market is considered only the investment oppor- tunity for retail investors. In 2009, Capital Market Authority (CMA) approved the trading of Sukuk (Islamic bond) and traditional bonds in Saudi Arabia, but only for institutional investors. Finally, it is important to mention that there is no short selling in Saudi stock market. Short selling plays a significant role in price corrections. [Hong and Stein, 2003] suggest that because of short-sales constraints, bearish investors do not initially participate in the market and their information is not revealed in prices. If short sale investors cannot participate in the market, bullish investors may keep buying stocks which leads to an in- crease in stock prices. For those reasons, it is questionable to just replicate U.S. asset-pricing models in Saudi Arabia.

3 Literature Review

[Fama and French, 1993] show that excess market returns, size factor (SMB), and book-to-market factor (HML) can explain expected returns. [Ferson and Harvey, 1999] show that the three-factor model of [Fama and French, 1993] fails to explain conditional expected returns. [DanieL and Titman, 1997] find that expected returns can be explained better by using firm characteristics rather than factor loadings from the [Fama and French, 1993] model. In response to [DanieL and Titman, 1997], [Davis et al., 2000] argue that the results in [DanieL and Titman, 1997] paper are subsample-specific. There are also contrary opinions when it comes to interpretation of these factors. Fama and French interpret the three-factors model as risk factors. However, [Lakonishok et al., 1994] and [Haugen, 1995] argue that size and value effects are due to the overreaction of investors to corporate news rather than compensation for risk bearing. They argue that investors systematically overreact to recent corporate news, and they irrationally anticipate high or low growth into the future which leads to undervaluation of value stocks and overvaluation of growth stocks. Beside Fama and French three-factor model, [Carhart, 1997] develop a four-factor model, which includes a momentum factor, to capture the patterns in U.S average returns. [Fama and French, 2015] develop 5-factor model that is related to investment and profitability.

Our work is also related to recent studies on global asset pricing. [Asness et al., 2013] in their paper " Value and Momentum Everywhere" find that value and momentum return premia across eight international markets. [Fama and French, 2012] examine the returns to size, value, and momentum in individual stocks across global equity markets and find consistent risk premia across markets. [Fama and French, 2012] examine the returns to size, value, and momentum in individual stocks across global equity markets and find value and momentum premiums across markets, except for Japan. [Moskowitz et al., 2012] provide global evidence of "time series momentum", which is a timing strategy using each asset's own past returns.

4 Data and Methodology

We obtain our data from Saudi Stock Exchange (Tadawul) and Capital IQ. The data is daily stock prices of Saudi companies and their financial statements for the periods 2006-2018. The data is available on Tadawul' s website as well. The monthly treasury bill rates data is obtained from Kenneth R. French for the period 2005-2018. After excluding firms with missing stock prices and some items of financial statements data, the number of companies in our sample is 140 companies in our sample.

4.1 Shariah-Compliance (Islamic Classification)

We obtain the data of Shariah (Islamic) stock classification from the Islamic scholar Dr. Al-Fozan for the period 2006 - 2015.[4] He is well known in Saudi Arabia as a Shariah scholar and an expert in Saudi stock market when it comes to classification. The Shariah classification reports are updated

[4] [Alhomaidi et al., 2019] use Dr.Al-Fozan's Islamic classification.

annually be- cause some companies move from one category to another according to the aforementioned criteria. Thus, we update the sample to match Shariah classification reports. These reports are publicly available.

4.2 Variable Construction

Following [Fama and French, 1993] and [Fama and French, 2012], we construct Market premium, SMB, HML, and WML (winner – loser). The computation of market to book ratio is the current stock price of the outstanding shares divided by the book value of shares. We classify firms by size, big and small. we consider top half and bottom half as threshold, so we use the median to separate between big and small firms every month. We construct value - growth returns for small and big firms, HMLS = SV–SG and HMLB = BV–BG, and HML is the equal- weight average of HMLS and HMLB. Momentum is the stock return for the past 11 months, excluding the most recent month. We also construct winner - loser returns for small and big stocks, WMLS = SW ˘SL and WMLB = BW ˘BL, and WML is the equal-weight average of WMLS and WMLB.

We use different measures for portfolio analysis. Following [Kumar, 2009], we estimate idiosyncratic volatility as the variance of the residuals from regress- ing stock i daily excess returns using [Fama and French, 1993] three-factor as follow:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t} MKT + s_{i,t} SMB + h_{i,t} HML + \varepsilon_{i,t} \quad (1)$$

The variance of the residuals $\varepsilon_{i,t}$ estimated using trailing 60 daily residual of

Fama and French three factor model. We calculate illiquidity using Amihud's measure, which is the time-series average of absolute daily return divided by daily volume. To consider nonsynchronous trading, we follow [Scholes and Williams, 1977], [Dimson, 1979], and [Bali et al., 2011], and we use the lag and lead of the market portfolio as well as the current market when estimating market beta:

$$R_{i,d}-r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d-1}-r_{f,d-1}) + \beta_{2,i}(R_{m,d}-r_{f,d}) + \beta_{3,i}(R_{m,d+1}-r_{f,d+1}) + \varepsilon_{i,d} \quad (2)$$

where $R_{i,d}$ is the return on stock i on day d, $R_{m,d}$ is the market return on day d, and $r_{f,d}$ is the risk-free rate on day d. We estimate this equation for each stock using daily return within a month. The market beta of stock i in month t is defined as

$$\hat{\beta}_i = \hat{\beta}_{1,i} + \hat{\beta}_{2,i} + \hat{\beta}_{3,i} \quad (3)$$

Size is the market capitalization calculated as the stock closing price at the end of the year times the number of shares outstanding. Return on equity (ROE) is equal to profit margin multiplied by asset turnover multiplied by financial leverage. Operating profitability (OP) is Fama and French's operating profitability measure, which is defined by the following: OP of year t is annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity for the last fiscal year end in t-1. Leverage is equal to total assets divided by total equity. Asset turnover is calculated by dividing sales by total assets. Log sales to book is calculated by adding the log of sales over stock price to the log of stock price value over book value. The monthly oil returns are calculated using daily Brent crude oil prices, at which Saudi oil is sold. Oil Return beta is a coefficient, obtained from monthly regressions of an individual stock return on oil return using a window of 24 months. We construct this variable because oil play an important role in Saudi economy.

5 Empirical Work and Results

We start the analysis with a summary statistic using the entire sample of Saudi stock market. Table 13 shows the size of Saudi firms ranges from small-cap stocks to large-cap stocks. The measure of value factor, sales to price, has a mean of 0.567, and the range between lowest and highest is large. The mean of illiquidity measure is 0.009, indicating that Saudi stocks are liquid in general. The mean of leverage ratio is 2.382, indicating that Saudi firms depend on both debt and equity financing.

5.1 Shariah Compliance and Lottery Features:

The Descriptive statistics of Islamic and non-Islamic portfolios are presented in Panel B, table 2. The mean market capitalization of conventional stocks is higher (19417) than that of Shariah-compliant firms (6420). Shariah-compliant firms exhibit higher profitability ratios than conventional counterparts. In terms of stock liquidity and trading activity, although Shariah-compliant stocks have slightly higher illiquidity statistics compared to conventional stocks, Shariah- compliant stocks are more actively traded, as indicated by their higher average turnover ratio. In addition, Shariah-compliant firms accounts for around 50% of the entire sample.

Table 2, panel C, presents summary statistics of different measures sorted by lottery-type stocks. We separate firms into lottery-type stocks and nonlottery- type stocks, based on [Bali et al., 2011]. The size of nonlottery-like stocks exhibits higher variance than that of lottery -like stocks. The mean market capitalization of nonlottery-type firms is higher (15066) than that of lottery-type firms (8810). The nonlottery-type stocks exhibit higher profitability ratios than non- lottery counterparts. In terms of stock liquidity and trading activity, lottery-like stocks are more actively traded, as indicated by their higher average turnover ratio, and they also have similar illiquidity to nonlottery-type stocks. In addition, lottery-like stocks have a higher number of investors than their nonlottery counterparts. the data of number of investors is only for the period 2010-2015.

5.1.1 Persistent

Islamic and lottery-like (MAX) are different characteristics, and it is important to differentiate between these characteristics. The main difference between Shariah and lottery characteristics in Saudi stock market is that MAX is very transitory while Shariah is very persistent over time. Table 15 shows the persistence of both characteristics. Panel A provides the correlations of the cross- section of MAX and Shariah variables versus their lags. The correlation of the cross-section of MAXt versus MAX t-J, J (months) = 1, 2, 3, 6, 12, 24, 36, 48, 60, becomes weaker as the number of lagged-months increases. By following [Bali et al., 2011], we create three portfolios sorted by MAX; lowest, middle, and highest. Highest MAX dummy variable, which is highest maximum daily returns over the past one month, represents lottery-type stocks and nonlottery-type stocks otherwise. The correlation of the cross-section of highest MAX versus its lags is very tran- sitory. On the contrary, the correlation of the cross-section of Shariah versus its lags is almost 100%, and it is very persistent over time. It is clear that MAX is not persistent (fast-moving) while Shariah is persistent.

For further investigation, we report transition probabilities for both Shariah and lottery-like characteristics. Table 16 reports the probability of transitioning from previous state of lottery to next state using different lagged periods. The proba- bility of lottery-like stock at time t-1 becoming nonlottery-like stocks at time t is 55%. This percentage increases as the number of lagged-periods increases. For instance, the probability of lottery-like stock at time t-24 becoming nonlottery- like stock at time t is 64. On the contrary, table 17 shows that probability of Shariah-compliant stock at time t-1 remaining Islamic stock at time t is 100%. It is so obvious that Shariah characteristics is very persistent while MAX is very transitory (fast-moving). This means that high MAX, which is a proxy for lottery-like characteristics, captures recent positive news, which grabs investor attention as measured by an increased investor base and increased liquidity.

5.1.2 Empirical Proportions

We want to investigate whether we have overlap between lottery-like stocks and Shariah stocks. It is important to know the probability of a lottery-like stock being an Islamic stock, and vice versa, because we want to make sure that when we examine the effect of lottery-like characteristic, we do not capture the effect of the Islamic characteristic. Table 18 reports the proportion of Islamic and lottery-like stocks among the entire sample, lottery-like portfolio, shariah- compliant portfolio, and their non-counterparts. The results show that half of the entire sample is Shariah-compliant while 32% of the entire sample is lottery-like stocks. In lottery-like portfolio, Islamic stocks account for 48%, which is almost half of the portfolio. Similarly, 53% of nonlottery-like portfolio is Islamic stocks. On the other hand, lottery-like stocks accounts for 30% of Shariah-compliant portfolio. Likewise, 35% of non Shariah-compliant portfolio is lottery-like stocks. The results suggest that it is not necessary for lottery-like stocks to be Shariah-compliant, and vice versa, as lottery-like stocks account for only one third of the entire Shariah-compliant portfolio. This is also supported by the fact that less than half of lottery-like portfolio is Islamic stocks. The statistics suggest that lottery-like and Shariah are different characteristics.

5.1.3 Breadth of ownership

By following [Alhomaidi et al., 2019], we conduct multivariate analysis explaining breadth of ownership between lottery-type stocks and nonlottery-type stocks, which is presented in table 21. More specifically, we run two-step

[Fama and MacBeth, 1973] regressions. In the first step, we run a cross-sectional regression of the log of number of investors on lottery-like stock dummy and subsets of other control variables. In the second step, we do the time-series averages of the monthly cross-sectional regression coefficients. Consistent with univariate results reported in Table 2, we find that lottery-like stocks attract a larger number of investors than nonlottery-like stocks in the Saudi equity market, as the coefficient on the lottery dummy variable is positive and statistically significant at the 1% level across all model specifications. The coefficients on the lottery dummy variables suggest that stocks with lottery-features have 20 to 10 percent more investors than a nonlottery-type stocks, after controlling for size, profitability, trading activity, and risk effect. The coefficient on lottery dummy is still positive and significant even after including Islamic dummy variable, and the magnitude of coefficient is larger than the magnitude of coefficient on Islamic dummy, indicating that stocks with lottery-features have more investors than Shariah-compliant stocks.

5.1.4 Stock liquidity and turnover

Table 22 presents the results from the multivariate analysis testing the relationship between lottery-type stocks and liquidity and trading in Saudi stock exchange, following [Alhomaidi et al., 2019]. Consistent with univariate results reported in Table 2, lottery stocks have higher liquidity than nonlottery-like stocks in the Saudi market. Using the illiquidity measure, the lottery dummy coefficient is consistently negative and statistically significant across all model specifications, which indicates that lottery-type stocks have lower illiquidity, or higher liquidity, than their nonlottery-like stocks counterparts. The same conclusion can be drawn using stock turnover as the dependent variable; lottery-like stocks have stock turnover ratios that are higher than those of non-lottery stocks. The results still hold even after controlling Islamic dummy variable. This indicates that stocks with lottery-like features receive stronger investor recognition than non-lottery-like stocks as measured by a broader investor base and higher liquidity. For further investigation, we examine whether MAX, which is a proxy for lottery-like features, dominates Islamic variable in terms of capturing retail investors' attentions. We conduct a portfolio analysis sorted by Shariah and Lottery. Within the Shariah group, we report the monthly average return and standard deviation of both lottery-like portfolio and non-lottery-like portfolio. Then, we examine if they have significantly different monthly average returns. Table 19 exhibits a clear monotonic pattern in the monthly average returns. In Shariah-compliant portfolio, the monthly average returns of the non-lottery-like portfolio is 0.55% while the average monthly return of the lottery-like portfolio is -0.726%, and the difference in the two average returns is strongly significant, at 5% level. In contrast, there is no significant difference in the monthly average returns between non-lottery-like portfolio and lottery-like portfolio within non-Shariah-compliant portfolio.

5.2 Profitability Effect:

5.2.1 Sales-to-Book Effect

The above decomposition analysis shows a significant relation between sales- to-price ratio and future returns. This leads us to examine the relation more in-depth. We investigate the effect of sales-to-book ratio in Saudi stock market. Sales-to-Book is calculated by multiplying the ratio of sales-over-stock-price by the ratio of "stock-price-over-book-value". For the portfolio analysis, we create and form four different portfolios: (1) firms with highest sales-to-book ratio, (2) firms with high sales-to-book ratio, (3) firms with low sales-to-book, and (4) firms with lowest sales-to-book. The same approach of M/B ratio is used for stocks with high and low sales-to-book ratios. Stocks with highest sales-to-book ratio exhibit higher average monthly returns than stocks with lowest sales-to- book ratio. Table 14 represents the average monthly return, standard deviation of the lowest (Quartile 1), low (Quartile 2), high (Quartile 3), and highest (Quartile 4) portfolios for sales-to-book as well as t-statistic of the difference in means of lowest and highest quartile portfolio (Quartile 1 - Quartile 4). There is a monotonic increase in the monthly average returns from lowest-quartile portfolio to highest-quartile portfolio. The mean of monthly returns of the value- weighted lowest-quartile portfolio is -0.38% while the average monthly returns of value-weighted highest-quartile portfolio is 1.057%, and the difference in the two returns is strongly significant at 5% level. Also, the average monthly returns of equally-weighted portfolios increase monotonically from lowest-quartile portfolio to the highest-quartile portfolio. The difference between the two-sample means is significant at level 1%.

For further analysis, we run two-step [Fama and MacBeth, 1973] regressions. We run a cross-sectional regression of stock return in each month on subsets of lagged sales-to-book in the previous month including other control variables. In the second step, we do the time-series averages of the monthly cross-sectional regression coefficients. In the univariate regressions in Table 23 and 24, the coefficients on sales-to-book are positive and statistically significant at 1% level. When we include a set of control variables, the coefficients on sales-to-book are still positive and statistically significant. This indicates that high S/B stocks tend to outperform. These results hold for both equally-weighted and value-weighted portfolios.

5.2.2 Return on Equity (ROE)

We use different measures of profitability to make sure that profitability effect exists in Saudi stock market. We follow the same approach of sales-to-book ratio analysis. We create eight portfolios sorted by ROE for both equally-weighted and value-weighted portfolios. Then, we run two-step [Fama and MacBeth, 1973] regressions. The definition of roe is that profit margin multiplied by asset turnover multiplied by financial leverage. We define return on equity (ROE) $= log\ (1 + roe)$.

Stocks with high ROE exhibit higher average monthly returns than stocks with low ROE. Table 3 represents the average monthly return, standard deviation of the lowest (Quartile 1), low (Quartile 2), high (Quartile 3), and highest (Quartile 4) portfolios for ROE as well as t-statistic of the difference in means of lowest and highest quartile portfolio (Quartile 1 - Quartile 4). There is a mono- tonic increase in the monthly average returns from lowest-quartile portfolio to highest-quartile portfolio. The mean of monthly returns of the value-weighted lowest-quartile portfolio is -0.405% while the average monthly returns of value- weighted highest-quartile portfolio is 1.402%, and the difference in the two re- turns is statistically significant at 1% level. Also, the average monthly returns of equally-weighted portfolios increase monotonically from lowest-quartile port- folio to the highest-quartile portfolio. The difference between the two-sample means is statistically significant.

We run two-step [Fama and MacBeth, 1973] regressions. We run a cross-sectional regression of stock return in each month on subsets of lagged ROE in the previous month including other lagged control variables. In the second step, we do the time-series averages of the monthly cross-sectional regression coefficients. In model 1 in table 25, the coefficients on ROE are positive and statistically significant. When we include a set of other control variables in model 2, the coefficients on ROE are still positive and statistically significant at 1% level. This indicates that stocks with high ROE tend to outperform, this is completely consistent with the results of sales-to-book ratio.

5.2.3 Operating Profitability (OP)

As a robustness check, we also use another different measure of profitability to make sure that profitability effect exists in Saudi stock market.

We follow Fama and French’s operating profitability measure in [Fama and French, 2015], their definition of operating profitability (OP) is the following: "OP for June of year t is annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity for the last fiscal year end in t-1." We follow the same approach of sales-to-book ratio analysis. We create eight portfolios sorted by OP for both equally-weighted and value-weighted portfolios. Then, we run two-step [Fama and MacBeth, 1973] regressions. The following section shows the results of this analysis.

Stocks with high operating profitability exhibit higher average monthly returns than stocks with low operating profitability. Table 3 represents the average monthly return, standard deviation of the lowest (Quartile 1), low (Quartile 2), high (Quartile 3), and highest (Quartile 4) portfolios for OP as well as t-statistic of the difference in means of lowest and highest quartile portfolio (Quartile 1 - Quartile 4). The mean of monthly returns of the value-weighted lowest-quartile portfolio is 0.196 % while the average monthly returns of value-weighted highest- quartile portfolio is 1.446%, and the difference in the two returns is statistically significant at 5% level.

We run two-step [Fama and MacBeth, 1973] regressions. We run a cross-sectional regression of stock return in each month on subsets of lagged operating profitability in the previous month including other lagged control variables. In the second step, we do the time-series averages of the monthly cross-sectional regression coefficients. In model 3 in table 25, we run stock return on OP and some control variables including size, market beta, oil return beta, and the coefficients on OP are positive and statistically significant at 1% level. When we include a set of other control variables in model 4, the coefficients on OP are still positive and statistically significant at 1% level. This indicates that stocks with high OP tend to outperform, this is completely consistent with the results of sales-to-book ratio. As we can see from the above profitability analysis, profitability effect appears to be present in Saudi Arabia. Our results are robust to using different measures of profitability, even after controlling for other effects including size, idiosyncratic variance, market beta, oil return beta, momentum, illiquidity, and growth effects. That means that stocks with high profitability ratios tent to outperform in Saudi Arabia.

5.3 Islamic Classification

We examine whether profitability effect exists in Shariah compliant and non Shariah-compliant portfolios. We create four portfolios: (1) equally-weighted Shariah-compliant portfolio, (2) value-weighted Shariah-compliant portfolio, (3) equally-weighted non Shariah-compliant portfolio, (4) value-weighted non Shariah- compliant portfolio.

Table 26 reports that the time-series averages of the cross-sectional regression slope coefficients and the standard errors for value-weighted Shariah-compliant portfolios and value-weighted non Shariah-compliant portfolios. We run a firm- level cross-sectional regression of the return in each month on sales-to-book ratio and subsets of lagged one-month control variables that are defined above. In table 26, the coefficients on sales-to-book

(S/B) are positive and statistically significant at 1% level. When we include a set of control variables, the coefficients on sales-to-book (S/B) is positive and statistically significant. This indicates that profitability effect is very strong among Shariah-compliant stocks, which means that Shariah compliant-stocks with high S/B tend to outperform. These results hold for both equally-weighted and value-weighted portfolios. For non Shariah-compliant (conventional) portfolio, profitability effect is also observed among those stocks. In table 26, the coefficients on sales-to-book (S/B), in model 3, are positive and significant. When we include a set of control variables, the coefficients on sales-to-book (S/B), in model 4, is statistically significant. We find that the profitability effect also exists among conventional stocks. These results hold for both equally-weighted and value-weighted portfolios.

For further investigation, we create a variable that measure the effect of interaction between profitability effect and Shariah. Table 27 reports the results of a set of Fama-MacBeth regressions of monthly returns on lagged one-month profitability, Shariah dummy variable, interaction between profitability x Shariah, and other control variables. In model 1, the coefficient on the interaction term between S/B and Shariah dummy is positive and statistically significant at 10% level. However, when we include other control variables, the effect of interaction term is negative and insignificant. These results are consistent with our findings, which indicate that the profitability effect is not concentrated on Shariah-compliant portfolio. Profitability effect appears to be present in the entire sample, and it is not concentrated in Shariah-compliant portfolio. While [Alhomaidi et al., 2019] and [Merdad et al., 2015] show Islamic stocks receive stronger investor recognition than conventional stocks, we show that investor religious preferences may not increase the investor recognition of profitable firms.

5.4 Lottery-Like Stocks (MAX Effect)

We believe that profitability has different effects in lottery-like portfolio and nonlottery-like portfolio. Our beliefs are driven by the facts that lottery-like stocks attract more retail investors documented by [Han and Kumar, 2013a], and 90% of daily trades in Saudi equity market is executed by individuals, and gambling effect exists in Saudi stock market. Although we know that 90% of Saudi stocks are traded by individual investors, we do not know exactly which type of stocks retail investors invest in as Tadawul reports the 90% proportion for the whole market. [Alhomaidi et al., 2019] attempt to answer this question by using Islamic classification to capture retail investor effects since this type of stocks are more visible and familiar to retail investors in a such market. In the perspective of risk-taking behavior, we sort stocks by lottery and non-lottery- like stocks. By following [Bali et al., 2011], we use the maximum daily return (MAX) in a month as a proxy for lottery-like payoffs. We create three portfolios sorted by MAX; lowest, middle, and highest. Lottery-type stocks are those with highest maximum daily returns over the past one month. Nonlottery-type stocks are those with lowest maximum daily returns over the past one month. Then, by following [Alhomaidi et al., 2019] approach, we conduct an analysis of both portfolios.

Lastly, we examine whether profitability have different effects in lottery and nonlottery-like stocks.

Table 20 represents the average monthly return, standard deviation of nine portfolios sorted by MAX and S/B, and t-statistic of the difference in means. Stocks with high MAX and high S/B exhibit higher average monthly returns while stocks with high MAX and low S/B. The average monthly returns of a portfolio with high MAX and low S/B is -0.73% while average monthly returns of a portfolio with high MAX and high S/B is 0.60%, and the difference in the two returns is statistically significant at 10% level.

Table 28 reports that the time-series averages of the cross-sectional regression slope coefficients and the standard errors for value-weighted portfolios sorted by MAX. Table 28 shows the coefficients on S/B for the lowest MAX portfolio are insignificant across all model specifications. In contrast, the coefficients on S/B for highest MAX portfolio are positive and statistically significant across all model specifications. Table 29 reports the results of a set of Fama-MacBeth regressions of monthly returns on lagged one-month profitability, lottery dummy variable, interaction between profitability x lottery dummy, and other control variables. In model 1, the coefficient on the interaction term between S/B and lottery dummy is positive and statistically significant at 5% level. When we include other control variables, the effect of interaction term is still significant. These results indicate profitability effect is driven by stocks with lottery-like features.

As expected, the profitability effect is much more pronounced among lottery- like stocks. One possible interpretation of the evidence would be that the profitability effect in Saudi stock market are associated with transitory but gradual increases in the investor recognition of profitable firms triggered by recent positive news captured by MAX. In the present, there is limits to arbitrage, so profitability information incorporates into stock prices gradually. More positive information incorporates in stock prices than negative information, which ultimately leads to high returns. This is consistent with previous literatures ([Hong and Stein, 2003]; [Bali et al., 2011].

5.5 Tests of Asset Pricing Model

We want to evaluate multiple asset-pricing models to find the best model works in Saudi stock market. We use a common approach to examine the effectiveness of the asset-pricing models. We employ [Gibbons et al., 1989] (GRS) statistic to test the null hypothesis that all intercepts (α) jointly equal zero, 0 :i= 0 for all of i. It is undesirable to have a larger GRS statistic value when it comes to the performance of an asset-pricing model because it means that the intercepts jointly are different from zero. The larger value of GRS test indicates that the factors in that model do not explain the variation of stock returns. In other words, a larger value of GRS statistic means the larger joint values of those alphas, which means that the farther those alphas move away from zero, which indicates a poorer performance of the asset-pricing model.

Table 30 reports GRS tests and MAVA for eight different asset-pricing models. The factors of model 4 are HML and RMW, and this model has a better GRS value and MAVA compared to other models. This indicates that

HML (growth effect) and RMW (profitability effect) outperform other models, with GRS statistics of 25.628 and p-value close to zero. The other asset-pricing model that performs better in explaining the variation of returns based on GRS results and MAVA well is model 7, where the factors of that model are market premium, SMB, HML, and RMW. The GRS score of model 8 is 27.098, with p-value close to zero.

6 Conclusion

This study sheds new lights into the factors that drive the cross-sectional variation of stock returns in Saudi stock market. Saudi stock market was chosen because of some of its unique characteristics, such as the nature of its investors and the prevalence of Islamic investment models, and due to Saudi's importance as an emerging market, both which make it worth examining. We find that, a stock's lottery-like feature, as measured by the maximum daily return over the past month (MAX), is strongly associated with a short-term increase in its investor-base and liquidity, beyond the effect of Islamic classification. Firms with high operational profitability have significantly higher average returns than others, and this profitability effect is more pronounced among the stocks with high MAX. The evidence suggests that retail investors' short-term attentions have significant effects on the cross-section of Saud stock returns.

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Table 12: Descriptive Statistics of Sales-to-Book Ratio of All Firms

Year	N of Firms	Mean	SD	Min	p5	p25	p50	p75	p95	Max
2006	44	0.577	0.835	0.006	0.025	0.135	0.298	0.553	2.251	7.149
2007	59	1.245	2.225	0.008	0.036	0.327	0.575	1.225	4.560	19.700
2008	69	1.334	5.512	0.000	0.015	0.175	0.357	0.935	3.132	72.376
2009	77	1.070	1.549	0.000	0.011	0.326	0.579	1.227	3.608	16.124
2010	85	1.187	2.078	0.001	0.017	0.301	0.579	1.308	3.585	18.882
2011	123	1.719	5.374	0.003	0.061	0.359	0.744	1.435	5.472	64.652
2012	128	1.561	4.420	0.001	0.081	0.310	0.711	1.444	4.623	59.607
2013	136	1.522	2.386	0.005	0.072	0.324	0.844	1.755	5.228	27.164
2014	138	1.473	3.060	0.015	0.074	0.295	0.622	1.481	5.171	46.994
2015	140	1.417	3.878	0.001	0.084	0.275	0.636	1.436	4.224	57.456
2016	139	1.400	1.883	0.003	0.108	0.305	0.874	1.765	4.281	15.402
2017	140	1.085	1.260	0.007	0.072	0.260	0.681	1.425	3.615	8.964
2018	140	1.102	1.339	0.002	0.077	0.226	0.633	1.465	3.600	8.654
Total		1.347	3.199	0.000	0.056	0.273	0.643	1.432	4.206	72.376

Note: This table reports the average of S/B ratios of 140 firms listed in Saudi Stock Exchange (Tadawul). N of Firms represents the unique number of firms in the sample by period. Mean is the mean of the monthly average S/B ratios of the individual stocks. SD is the standard deviation. Sales-to-Book is calculated by multiplying the ratio of "sales over stock price" by the ratio of “stock price over book value".

Table 13: Descriptive Statistics of Different Measures

Panel A: the entire sample

Measure	Mean	Median	SD	Min	Max
Size	12,208	2,319	36,384	20	723,750
Sales/Price	0.576	0.318	1.082	0.000	34.739
ROE	0.143	0.145	0.903	-20.857	5.447
Operating Profitability	0.092	0.078	0.188	-2.172	0.893
Sales/Book	1.347	0.642	3.200	0.000	72.376
Illiquidity	0.009	0.003	0.266	0.000	32.169
Leverage	2.382	1.716	1.891	1.002	15.780
Asset Turnover	0.483	0.372	0.494	0.000	4.814

Panel B: Islamic and Non-Islamic Stocks

	Shariah-Compliant					Conventional				
Measure	Mean	Median	SD	Min	Max	Mean	Median	SD	Min	Max
Size	6420	2598	12865	20.412	126181	19417	2358	52896	68.676	723750
Sales/Price	0.592	0.272	1.553	0.002	34.739	0.504	0.379	0.573	0.000	4.056
ROE	0.191	0.1607	0.481	-5.060	2.768	0.104	0.161	1.091	-20.860	5.103
Operating Profitability	0.120	0.101	0.162	-0.462	0.706	0.079	0.076	0.220	-2.172	0.712
Sales/Book	1.605	0.593	4.817	0.002	72.376	1.165	0.788	1.425	0.000	14.222
Illiquidity	0.013	0.003	0.432	0.000	32.169	0.006	0.002	0.025	0.000	0.844
Leverage	1.860	1.440	1.298	1.002	10.807	2.745	2.287	2.287	1.013	15.779
Asset Turnover	0.595	0.416	0.642	0.002	4.813	0.390	0.365	0.286	0.000	1.684
Number of Firms	49	50	17	24	71	49	50	19	20	69

Panel C: Lottery-Type Stocks

	Lottery					Nonlottery				
Variable	Mean	Median	SD	Min	Max	Mean	Median	SD	Min	Max
Size	8810	1641	28748	22.032	489178	15066	3116	39498	23.166	581250
Sales/Price	0.589	0.332	1.113	0.000	32.184	0.543	0.293	1.007	0.000	30.609
ROE	0.111	0.123	1.023	-20.857	5.447	0.175	0.161	0.731	-20.857	5.447
Operating Profitability	0.072	0.064	0.229	-2.172	0.893	0.110	0.094	0.153	-0.825	0.893
Sales/Book	1.564	0.785	3.517	0.000	67.054	1.148	0.551	2.763	0.000	63.772
Illiquidity	0.007	0.003	0.045	0.000	2.816	0.007	0.002	0.019	0.000	0.844
Leverage	2.601	1.853	2.151	1.002	15.779	2.187	1.603	1.626	1.002	15.779
Asset Turnover	0.491	0.389	0.493	0.000	4.814	0.469	0.357	0. 490	0.000	4.813
Turnover	0.027	0.009	0.055	0.000	0.894	0.012	0.003	0.027	0.000	0.593
Log (Number of investors)	10.145	9.881	1.226	7.457	13.482	10.102	9.894	1.339	7.462	13.474

Note: This table reports mean, median, standard deviation, minimum, and maximum of different variables for the period 2006-2018. Size is the market capitalization calculated as the stock closing price at the end of the year times the number of shares outstanding (in *SAR* = $0.267). ROE is return on equity, and it is equal to profit margin multiplied by asset turnover multiplied by financial leverage Operating profitability (OP) is Fama and French's operating profitability measure, which is defined by the following: OP of year t is annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity for the last fiscal year end in *t* 1. Illiquidity is calculated using Amihud's measure (multiplied by), which is the time-series average of absolute daily return divided by daily volume. Leverage is equal to total assets divided by total equity. Asset turnover is calculated by dividing sales by total assets. Panel B shows summary statistics for Saudi stocks during the period from 2006 to 2015 sorted by based Shariah-compliant and conventional (non-Shariah-compliant) stocks. Panel C shows summary statistics for Saudi stocks during the period from 2006 to 2018 sorted by lottery-type stocks. By following Bali, Cakici, and Whitelaw (2011), we use the maximum daily return (MAX) in a month as a proxy for lottery-like payoffs. We create three portfolios sorted by MAX; lowest, middle, and highest. Lottery- type stocks are those with highest maximum daily returns over the past one month and Nonlottery-type stocks otherwise. Turnover is stock trading volume over total shares outstanding. Log number of investors are reported at the end of each month and only for the period from 2010-2015.

Table 14: Means for Different Portfolios

Sales-to-Book (EW)	Quartile 1 (Lowest)	Quartile 2	Quartile 3	Quartile 4 (Highest)	Difference (Q1) - (Q4)
Mean	-0.269	-0.161	0.154	1.041	-1.311
Standard Deviation	11.432	9.711	8.663	10.532	4.983
t - test					-3.178
Sales-to-Book (VW)					
Mean	-0.38	-0.282	0.044	1.057	-1.437
Standard Deviation	11.553	8.267	8.398	8.589	8.881
t - test					-1.96
ROE (EW)					
Mean	-0.405	-0.206	0.072	1.402	-1.808
Standard Deviation	13.346	10.942	8.446	7.601	8.426
t - test					-2.592
Operating Profitability (EW)					
Mean	0.196	0.429	0.749	1.446	-1.248
Standard Deviation	9.862	8.232	7.482	6.127	6.114
t - test					-2.363
Momentum (EW)					
Mean	0.801	0.561	0.877	0.472	0.328
Standard Deviation	9.298	7.803	7.223	7.248	5.574
t - test					0.682
Momentum (VW)					
Mean	1.102	0.308	1.095	0.793	0.309
Standard Deviation	8.897	6.836	6.812	6.831	6.226
t - test					0.575

Notes: This table represents the monthly average return of different portfolios sorted by different measures. Sales-to-Book is calculated by multiplying the ratio of "sales over stock price" by the ratio of "stock price over book value". ROE is equal to profit margin multiplied by asset turnover multiplied by financial leverage. Operating profitability is Fama and French's operating profitability measure, which is defined by the following: OP of year t is annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity for the last fiscal year end in t-1. Momentum is past 12-month cumulative raw return on a stock, skipping the most recent month. The sample period is from 2006-2018

Table 15: Persistence of MAX and Shariah

Panel A: Correlations of the Cross-Section of MAX and Shariah variables versus their lags.

	Correlation		
Lag (months)	**MAX**	**Highest MAX(Dummy)**	**Shariah**
1	0.1656	0.1702	1
2	0.1306	0.1539	1
3	0.1234	0.1391	1
6	0.1237	0.1262	1
12	0.0946	0.0999	0.9975
24	0.0578	0.0717	0.994
36	0.0626	0.0785	0.9888
48	0.0047	0.0511	0.9826
60	-0.001	0.0619	0.9769

Panel B: Autocorrelation of MAX

Year	**Correlation**
2006	-
2007	0.035
2008	-0.086
2009	-0.021
2010	0.121
2011	0.057
2012	0.144
2013	0.158
2014	0.091
2015	0.157
2016	0.15
2017	0.165
2018	0.136

Note: *Panel A* shows the correlation of the cross-section of MAX and Shariah variables versus their lags. MAX (continuous) is maximum daily returns over the past one month. Highest MAX dummy represents firms with top 1/3 of MAX. Shariah is an Islamic dummy variable equal to one if the firm is classified as Islamic or zero otherwise. *Panel B* shows a correlation to test autocorrelation of MAX. Each row of Corr represents the correlation between this year and the previous year.

Table 16: Transition Probability of Lottery-Type Dummy

State Transition Probabilities		Next State: Non-Lottery	Next State: Lottery
Previous States	*Panel A: Pr[Lottery t | Lottery t-1]*		
	Non-Lottery	72.78	27.22
	Lottery	55.49	44.51
	Panel B: Pr[Lottery t | Lottery t-3]		
	Non-Lottery	72.20	27.79
	Lottery	57.40	42.60
	Panel C: Pr[Lottery t | Lottery t-6]		
	Non-Lottery	72.05	27.94
	Lottery	57.96	42.03
	Panel D: Pr[Lottery t | Lottery t-12]		
	Non-Lottery	71.41	28.59
	Lottery	61.04	38.96
	Panel E: Pr[Lottery t | Lottery t-24]		
	Non-Lottery	72.40	27.60
	Lottery	64.38	35.96

Note: This table reports the transition probability that is the probability of transitioning from one state of lottery at time t-1, t-3, t-6, t-12, t-24 to another state of lottery at t (in months). Lottery dummy is firms with top 1/3 of MAX.

Table 17: Transition Probability of Shariah Compliance Dummy

State Transition Probabilities		**Next States**	
		Non-Shariah Compliance	Shariah Compliance
Previous States	Non-Shariah Compliance	99.98	0.02
	Shariah Compliance	0.00	100

Note: This table reports the transition probability that is the probability of transitioning from one state to another state of lottery at t (in months). Islamic dummy is Shariah dummy variable equal to one if the firm is classified as Islamic or zero otherwise.

Table 18: Descriptive Statistics

	Portfolio of Entire Sample	Lottery-Like Portfolio	Non Lottery-Like Portfolio	Shariah-Compliant Portfolio	Non Shariah-Compliant Portfolio
Panel A:					
Islamic	50%	48%	53%		
Non-Islamic	50%	52%	47%		
Panel B:					
Lottery	32%			30%	35%
Non-Lottery	68%			70%	65%

Note: This table reports the proportion of Islamic and lottery-like stocks among the entire sample, lottery-like portfolio, shariah-compliant portfolio, and their counterparts for a sample of 140 firms listed in Saudi stock exchange. By following Bali, Cakici, and Whitelaw (2011), we use the maximum daily return (MAX) in a month as a proxy for lottery-like payoffs. We create three portfolios sorted by MAX; lowest, middle, and highest. Lottery-type stocks are those with highest maximum daily returns over the past one month and Nonlottery-type stocks otherwise. Shariah is an Islamic dummy variable equal to one if the firm is classified as Islamic or zero otherwise. The sample period is from 2006-2015.

Table 19: Means for Different Portfolios

MAX (Shariah-Compliance Portfolio)	**Low (Non-Lottery Stocks) (1)**	**Middle (2)**	**High (Lottery Stocks) (3)**	**Difference (1) - (3)**
Mean	0.555	-0.119	-0.726	1.281
Standard Deviation	8.229	10.173	10.775	6.487
t - test				2.145
MAX (Non Shariah-Compliance Portfolio)				
Mean	-0.334	0.235	0.218	-0.549
Standard Deviation	9.492	12.014	10.005	6.996
t - test				-0.853

Notes: This table represents the monthly average return, standard deviation of the low, middle, and high MAX portfolios sorted by Shariah-compliance as well as t-statistic of the difference in means of low and high MAX portfolios. The portfolios are value-weighted. By following Bali, Cakici, and Whitelaw (2011), we use the maximum daily return (MAX) in a month as a proxy for lottery-like payoffs. We create three portfolios sorted by MAX; lowest, middle, and highest. Lottery-type stocks are those with highest maximum daily returns over the past one month and Nonlottery-type stocks otherwise. Shariah-compliant firms are those classified as Islamic stocks and non Shariah-compliance otherwise.

Table 20: Means and Difference for MAX & S/B Portfolios

	Mean			Difference
Variable	Low MAX (1)	Medium MAX (2)	High MAX (3)	**(1) - (2)**
Low S/B (4)	-0.36%	0.02%	-0.73%	0.37%
Medium S/B (5)	-0.09%	0.22%	-0.05%	-0.04%
High S/B (6)	0.36%	0.15%	0.60%	-0.24%
Difference (4) - (6)	-1.42%	-0.13%	-1.33%*	

Notes: Mean represents the monthly average return of each portfolio. The portfolios are value weighted. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 21: Breadth of Ownership

Independent Variable	Dependent Variable = Log (Number of investors) (1)	(2)	(3)	(4)
Lottery Dummy	0.20	0.12	0.10	0.11
	(6.13)	(3.91)	(3.36)	(3.45)
Islamic Dummy				0.03
				(1.40)
Size	0.36	0.49	0.49	0.49
	(57.85)	(67.29)	(65.74)	(62.73)
S/B	0.13	0.14	0.15	0.15
	(19.35)	(20.48)	(20.07)	(21.30)
Log (Age)	-0.69	-0.64	-0.54	-0.53
	(-4.96)	(-4.93)	(-4.67)	(-4.64)
MOM	-0.07	-0.09	-0.07	-0.07
	(-1.51)	(-2.14)	(-1.55)	(-1.51)
INVP	19.74	17.96	16.37	16.59
	(44.37)	(45.92)	(47.93)	(46.93)
Log (Turnover)		0.22	0.18	0.18
		(20.23)	(15.09)	(14.93)
DD			-0.31	-0.31
			(-11.75)	(-11.83)
R-squared	0.26	0.30	0.31	0.32

Note: This table reports the time-series averages of the cross-sectional regression slope coefficients and the standard errors. We run a firm-level cross-sectional regression of the log of number of investors in each month on lottery-like stock dummy and subsets of other control variables. Explanatory variables are a lottery dummy variable which equals to one if the firm is classified as lottery-like and zero otherwise, Islamic dummy is Shariah dummy variable equal to one if the firm is classified as Islamic or zero otherwise, Size is the natural log of firm market value, S/B is the lagged log of sales over book, which is calculated by adding the log of "sales over stock price " to the log of " stock price value over book value. , Age is the number of months the firm appears in our data, MOM is momentum, Invp is the inverse of share price, Turnover is calculated as the ratio of traded stock volume over firm total shares outstanding, and DD is a dummy variable that equals one if the firm pays dividends and zero otherwise. Regression (4) represent results of sample period from 2006-2015 while the first three regressions represent the results of sample period from 2006-2018. Numbers shown in parentheses are t-statistics.

Table 22: Stock Liquidity and Trading Activity

	Dependent Variable = Log (ILLIQ)			Dependent Variable = Log (Turnover)		
Independent Variable	(1)	(2)	(3)	(1)	(2)	(3)
Lottery Dummy	-0.22	-0.13	-0.14	0.39	0.41	0.41
	(-8.43)	(-5.93)	(-6.08)	(11.89)	(12.37)	(12.21)
Islamic Dummy			-0.08			-0.06
			(-5.87)			(-2.65)
Size	-0.32	-0.44	-0.45	-0.78	-0.75	-0.75
	(-20.76)	(-30.16)	(-29.49)	(-55.41)	(-49.00)	(-50.28)
S/B	0.08	0.05	0.04	-0.11	-0.08	-0.08
	(11.80)	(6.70)	(6.32)	(-13.49)	(-9.38)	(-9.20)
Log (Age)	0.06	0.03	0.03	-0.08	-0.08	0.06
	(1.66)	(1.00)	(0.86)	(-3.39)	(-2.67)	(-2.31)
INVP	-37.99	--38.59	-39.23		9.36	9.21
	(-19.88)	(-20.13)	(-19.75)		(7.01)	(7.34)
Log (Turnover)		-14.92	-15.18			
		(-10.72)	(-10.97)			
R-squared	0.49	0.57	0.58	0.57	0.58	0.59

Note: This table reports the time-series averages of the cross-sectional regression slope coefficients and the standard errors. We run a firm-level cross-sectional regression of Amihud(2002) log(Illiquidity) or Saudi stock turnover in each month on lottery-like stock dummy and subsets of other control variables. Explanatory variables are a lottery dummy variable which equals to one if the firm is classified as lottery-like and zero otherwise, Islamic dummy is Shariah dummy variable equal to one if the firm is classified as Islamic or zero otherwise, Size is the natural log of firm market value, S/B is the lagged log of sales over book, which is calculated by adding the log of "sales over stock price " to the log of " stock price value over book value. , Age is the number of months the firm appears in our data, variance is idiosyncratic variances of the individual stocks, which are calculated using trailing 60 daily residual of Fama and French three factor model, Invp is the inverse of share price, and turnover is calculated as the ratio of traded stock volume over firm total shares outstanding. Regressions (3) represent results of sample period from 2006-2015 while the first three regressions represent the results of sample period from 2006-2018. Numbers shown in parentheses are t-statistics.

Table 23: Fama–MacBeth Return Regressions - (EW)

	Dependent Variable = Return								
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
S/B	0.41							1.242	1.43
	(3.39)							(4.53)	(4.94)
MOM		-1.22						-1.75	-1.665
		(-1.65)						(-2.48)	(-2.12)
Size			-0.08					0.06	-0.05
			(-0.40)					(0.43)	(0.35)
Mkt Beta				0.11				-0.04	-0.08
				(0.43)				(-0.21)	(-0.42)
S/P					0.23			-1.02	-1.200
					(2.01)			(-3.48)	(3.96)
ILLIQ						-30.91			-24.66
						(-1.02)			(-0.96)
Oil Return Beta							0.35		0.19
							(0.69)		(0.41)
R-squared	0.02	0.04	0.08	0.03	0.02	0.04	0.05	0.17	0.23

Note: This table reports the time-series averages of the cross-sectional regression slope coefficients and the standard errors (equally-weighted). We run a firm-level cross-sectional regression of the return in each month on subsets of lagged variables in the previous month including control variables that are defined in the Appendix. S/B is the lagged log of sales over book, which is calculated by adding the log of "sales over stock price " to the log of " stock price value over book value. MOM is momentum. Mkt Beta is market beta. S/P is the log of sales to price. ILLIQ is illiquidity. Oil Return beta is coefficient, obtained from monthly regressions of an individual stock return on oil return using a window of 24 months. The sample period is from 2006 to 2018. Numbers shown in parentheses are t-statistics.

Table 24: Fama–MacBeth Return Regressions - (VW)

	Dependent Variable = Return								
Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
S/B	0.34							0.98	0.99
	(1.46)							(3.16)	(3.20)
MOM		0.01						-0.79	-0.22
		(0.01)						(-0.91)	(-0.24)
Size			-0.04					-0.02	-0.145
			(-0.28)					(-0.16)	(-1.19)
Mkt Beta				-0.96				-0.28	-0.14
				(-1.47)				(-0.94)	(-0.48)
S/P					0.08			-0.798	-0.87
					(0.34)			(-2.57)	(2.78)
ILLIQ						30.68			-58.29
						(0.59)			(-2.12)
Oil Return Beta							0.42		-0.75
							(0.59)		(-1.12)
R-squared	0.08	0.09	0.10	0.08	0.08	0.04	0.11	0.30	0.37

Note: This table reports the time-series averages of the cross-sectional regression slope coefficients and the standard errors (value-weighted). We run a firm-level cross-sectional regression of the return in each month on subsets of lagged variables in the previous month including control variables that are defined in the Appendix. S/B is the lagged log of sales over book, which is calculated by adding the log of "sales over stock price " to the log of " stock price value over book value. MOM is momentum. Mkt Beta is market beta. S/P is the log of sales to price. ILLIQ is illiquidity. Oil Return beta is coefficient, obtained from monthly regressions of an individual stock return on oil return using a window of 24 months. The sample period is from 2006 to 2018. Numbers shown in parentheses are t-statistics.

Table 25: Fama–MacBeth Regressions - Profitability

	Dependent Variable = Return			
Independent Variable	(1)	(2)	(3)	(4)
ROE	2.57	2.28		
	(2.75)	(2.76)		
OP			4.27	3.15
			(3.95)	(2.33)
Size	-0.16	-0.19	-0.12	-0.19
	(-1.07)	(-1.60)	(-0.94)	(-1.61)
Mkt Beta	-0.05	-0.18	-0.07	-0.10
	(-0.12)	(-0.63)	(-0.21)	(-0.35)
ILLIQ	-34.43	-61.33	-71.58	-65.87
	(-1.05)	(-2.31)	(-2.66)	(-2.33)
Oil Return Beta	-0.17	-1.03	-0.54	-1.02
	(-0.26)	(-1.53)	(-0.67)	(-1.54)
B/M		-0.68		-0.57
		(-2.40)		(-1.56)
MOM		-0.34		-0.44
		(-0.37)		(-0.46)
R-squared	0.31	0.38	0.30	0.39

This table reports the time-series averages of the cross-sectional regression slope coefficients and the standard errors for both values weighted and equally weighted. We run a firm-level cross-sectional regression of the return in each month on subsets of lagged variables in the previous month including control variables that are defined in the Appendix. ROE is equal to profit margin multiplied by asset turnover multiplied by financial leverage. ROE shown in this table is log(1+ROE). Operating profitability (OP) is Fama and French's operating profitability measure, which is defined by the following: OP of year t is annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity for the last fiscal year end in t-1. MOM is momentum. Mkt Beta is market beta. ILLIQ is illiquidity. Oil Return beta is coefficient, obtained from monthly regressions of an individual stock return on oil return using a window of 24 months. Numbers shown in parentheses are t-statistics.

Table 26: Fama–MacBeth Regressions – Profitability and Shariah

	Dependent Variable = Return			
	Shariah-Compliance		Non Shariah-Compliance	
Independent Variable	(1)	(2)	(3)	(4)
S/B	1.37	1.36	1.61	1.32
	(3.55)	(3.46)	(2.99)	(2.42)
MOM	-1.18	-0.40	-0.37	0.72
	(-1.06)	(-0.36)	(-0.28)	(0.43)
Size	-0.07	-0.18	-0.18	-0.21
	(-0.34)	(-0.71)	(-1.09)	(-1.02)
Variance	0.03	-0.06	-0.14	-0.145
	(0.26)	(-0.55)	(-1.33)	(-1.23)
Mkt Beta	0.12	0.13	-1.12	-0.93
	(0.58)	(0.36)	(-1.71)	(-1.69)
S/P	-1.268	-1.26	-1.59	-1.34
	(-2.90)	(-2.83)	(-3.12)	(-2.60)
ILLIQ		-97.39		-32.63
		(-1.72)		(-0.56)
Oil Return Beta		-0.16		-0.92
		(-0.21)		(-0.90)
R-squared	0.40	0.46	0.52	0.59

Note: This table reports the time-series averages of the cross-sectional regression slope coefficients and the standard errors for value-weighted portfolios. We run a firm-level cross-sectional regression of the return in each month on subsets of lagged variables in the previous month including control variables by using two subsamples; Shariah-compliant stocks and non Shariah-compliant stocks. S/B is the lagged log of sales over book, which is calculated by adding the log of "sales over stock price " to the log of " stock price value over book value. Variance is idiosyncratic variance. MOM is momentum. Mkt Beta is market beta. S/P is the log of sales to price. ILLIQ is illiquidity. Oil Return beta is coefficient, obtained from monthly regressions of an individual stock return on oil return using a window of 24 months. Numbers shown in parentheses are t-statistics.

Table 27: Fama–MacBeth Regressions – Profitability and Shariah

	Dependent Variable = Return	
Independent Variables	(1)	(2)
S/B	0.17	1.95
	(1.71)	(3.88)
Shariah Dummy	-0.19	-0.59
	(-0.11)	(-0.30)
Profitability x Shariah	0.28	-0.49
	(1.90)	(-1.01)
Size	0.01	-0.04
	(0.05)	(-0.24)
MOM	-1.07	-1.99
	(-0.97)	(-1.45)
Market Beta		-0.71
		(-1.83)
S/P		-1.82
		(-3.70)
ILLIQ		-13.93
		(-0.25)
Size x Shariah	-0.02	-0.02
	(-0.10)	(-0.08)
MOM x Shariah	0.78	1.03
	(0.75)	(0.75)
Market Beta x Shariah		1.06
		(2.22)
S/P x Shariah		0.59
		(1.33)
ILLIQ x Shariah		-68.14
		(-1.12)
R-squared	0.20	0.32

Note: This table reports the time-series averages of the cross-sectional regression slope coefficients and the standard errors for equally-weighted portfolios. We run a firm-level cross-sectional regression of the return in each month on subsets of lagged variables in the previous month including control variables. S/B is the lagged log of sales over book, which is calculated by adding the log of "sales over stock price " to the log of " stock price value over book value. MOM is momentum. Mkt Beta is market beta. S/P is the log of sales to price. ILLIQ is illiquidity. Numbers shown in parentheses are t-statistics.

Table 28: Fama–MacBeth Regressions - Profitability and Lottery

	Dependent Variable = Return			
	Lowest MAX		Highest MAX	
Independent Variable	(1)	(2)	(3)	(4)
S/B	0.35	-0.18	0.83	1.20
	(0.84)	(-0.39)	(1.68)	(2.13)
Size	0.28	0.46	0.05	0.038
	(1.46)	(2.11)	(0.26)	(0.15)
Variance	0.11	0.13	-0.12	-0.14
	(0.75)	(0.80)	(-1.22)	(-1.30)
Mkt Beta	0.09	-0.59	0.08	0.03
	(0.16)	(-0.95)	(0.24)	(0.08)
S/P	-049	0.18	-0.55	-0.97
	(-1.15)	(0.37)	(-1.05)	(-1.63)
ILLIQ		99.38		-164.35
		(1.58)		(-1.86)
Oil Return Beta		0.84		-0.20
		(0.76)		(-0.24)
R-squared	0.46	0.54	0.44	0.54

Note: This table reports the time-series averages of the cross-sectional regression slope coefficients and the standard errors for value-weighted portfolios sorted by MAX. We run a firm-level cross-sectional regression of the return in each month on subsets of lagged variables in the previous month including control variables that are defined in the Appendix. By following Bali, Cakici, and Whitelaw (2011), we use the maximum daily return (MAX) in a month as a proxy for lottery-like payoffs. We create three portfolios sorted by MAX; lowest, middle, and highest. Lottery-type stocks are those with highest maximum daily returns over the past one month, and nonlottery-type stocks are those with lowest maximum daily returns over the past one month. S/B is the lagged log of sales over book, which is calculated by adding the log of "sales over stock price " to the log of " stock price value over book value. Variance is idiosyncratic variance. Mkt Beta is market beta. ILLIQ is illiquidity. Oil Return beta is coefficient, obtained from monthly regressions of an individual stock return on oil return using a window of 24 months. The sample period is from 2006 to 2018. Numbers shown in parentheses are t-statistics.

Table 29: Fama–MacBeth Regressions – Profitability and Lottery

	Dependent Variable = Return	
Independent Variables	(1)	(2)
S/B	0.28	1.16
	(3.21)	(4.38)
Lottery Dummy	1.33	3.21
	(0.82)	(1.83)
Profitability x Lottery Dummy	0.28	0.97
	(1.97)	(1.68)
Size	0.01	0.03
	(0.08)	(0.19)
MOM	-0.24	-0.30
	(-0.35)	(-0.42)
Market Beta		0.12
		(0.54)
S/P		-1.01
		(-3.55)
ILLIQ		-19.75
		(-0.79)
Size x Lottery Dummy	0.04	-0.12
	(0.20)	(-0.58)
MOM x Lottery Dummy	-2.224	-3.21
	(-2.26)	(-2.55)
Market Beta x Lottery Dummy		-0.22
		(-0.64)
S/P x Shariah		-0.45
		(-0.76)
ILLIQ x Lottery Dummy		-121.69
		(-1.65)
R-squared	0.19	0.30

Note: This table reports the time-series averages of the cross-sectional regression slope coefficients and the standard errors. We run a firm-level cross-sectional regression of the return in each month on subsets of lagged variables in the previous month including control variables. Explanatory variables are a lottery dummy variable which equals to one if the firm is classified as lottery-like and zero otherwise. S/B is the lagged log of sales over book, which is calculated by adding the log of "sales over stock price " to the log of " stock price value over book value. Mkt Beta is market beta. ILLIQ is illiquidity. The sample period is from 2006 to 2018. Numbers shown in parentheses are t-statistics.

Table 30: The Performance of Different Asset-Pricing Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GRS test	36.414	27.243	27.528	25.628	36.623	58.952	27.098	27.775
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: This table reports on p-value of GRS test on the null that the alphas are jointly zero for eight different models. Model 1 is CAPM. Model 2 is Fama–French three-factor model. Model 3 is Carhart four-factor model. Factors in model 4 are HML and RMW (robust minus weak). Factors in model 5 are SMB, HML, and RMW. Factors in model 6 are market premium, HML, and RMW. Factors in model 7 are market premium, SMB, HML, and RMW. Factors in model 8 are market premium, SMB, HML, WML (winner minus loser), and RMW. The returns on these portfolios run on a monthly basis from 2006 to 2018.

Manuscript 3

Forecasting Stock Price Crashes: Islamic Classification and MAX - Evidence from Saudi Arabia

by

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Manuscript 3

Forecasting Stock Price Crashes: Islamic Classification and MAX - Evidence from Saudi Arabia

Abstract

This article investigates whether Islamic classification and MAX, defined as the maximum daily return over the past one month, exhibit a higher future crash risk in Saudi Stock Market. Saudi Stock Market was chosen because of some of its unique characteristics, such as the nature of its investors and the prevalence of Islamic investment models, and due to the importance of Islamic classification and MAX in this market, both which make it worth examining. The evidence shows that MAX is negatively associated with future crash risk after controlling for other predictors of crash risk. In contrast, the relation between Islamic classification and future stock price crash risk is weak.

1 Introduction

Despite a proliferation of crash risk research over the last ten years, there is very little research on crash risk in Saudi Stock Market. In the first and second chapters, we shed new lights into the unique features Saudi stock markets, which motivate us to examine this market. One of the distinguishing features of Saudi stock markets is the dominance of religious retail investors. According to Tadawul, 90 percent of Saudi stocks are traded by individual Muslim investors (see also Alhomaidi, et al., 2019).

In the context of retail investor attention, Merdad, et al. (2015) document Islamic effect in Saudi stock market and show that stocks of Shariah-compliant firms (Islamic stocks) and non-Shariah-compliant stocks (conventional stocks) behave differently in Saudi stock markets. Alhomaidi et al. (2019) show that the Islamic classification draws stronger investor recognition than conventional stocks as measured by a broader investor-base and higher liquidity. In the first chapter, we document gambling effect in Saudi Stock Market where retail investors overpay lottery-like stocks, which is somewhat unexpected (please see the first chapter). In the second chapter, we examine whether Islamic stocks and lottery-like stocks has an impact on profitability effect, and we document the moderating effects of the maximum daily return over the past one month (MAX) on the profitability effect in Saudi stock markets. Thus, it is interesting to investigate how well Islamic classification and MAX forecast future stock price crash risk in Saudi Stock Market.

Chen et al. (2001) and other literatures define stock price crash risk as related to negative skewness in the distribution of returns for individual stocks. Previous literatures view the accumulation of bad news (withholding bad news) play a crucial role in the formation of a stock price crash. Managers attempt to withhold or hide bad news for their own interests. For instance, they hide bad news for an extended period in order to maximize their compensations, protect employment and minimize litigation concerns emanating from bad news disclosures (Kothari et al., 2009). In the context of retail investor domination in a market, Wen et al. (2019) investigate the effect of retail investor attention on stock price crash risk in China. They show that firms with higher retail investor attention tend to have a lower future stock price crash risk. When a firm attracts individual investor's attention, the investor might seek more information about the firm (Gao, Wang, Wang, and Liu, 2018), which in turns mitigates the information asymmetry problem (Ding and Hou, 2015). The more information the individual investors obtain, the more difficult and more costly the managers of firms hide the bad news. For a firm with less retail investor attention, individual investors may seek less information about the company, and the executives are under low pressure to hide negative news from the public. As a result, the bad news will accumulate for a firm with low retail investor attention leading to greater future crash risk. This is how Wen et al. (2019) interpret their findings that firms with higher retail investor attention may have lower future firm-specific crash risks. Since Saudi stock market is dominated by retail investors, and Shariah-compliant stocks and lottery-like stocks attract more retail investors in Saudi stock market, and along the lines of reasoning by Wen et al. (2019), we would naturally expect that Islamic classification and MAX (a measure of lottery-like stocks) forecast future stock price crash risk.

On the contrary, we find that Shariah classification is not robustly associated with future crash risk. In NSKEW regression, the coefficient on Islamic dummy variable is not significant after including controlling for size, book-to-market, and other variables. However, MAX appears to be negatively associated with future crash risk in Saudi Stock Market. This is consistent with Wen et al. (2019) who find that stock price crash risk is significantly negatively associated with retail investor attention, indicating that retail investor attention can effectively decrease information asymmetry and, in turn, mitigate stock price crash risk.

2 Data and Methodology

We obtain our data from Saudi Stock Exchange (Tadawul) and Capital IQ. The data is daily stock prices of Saudi companies and their financial statements for the periods 2006-2018. The data is available on Tadawul's website as well. The monthly treasury bill rates data is obtained from Kenneth R. French for the period 2005-2018. After excluding firms with missing stock prices and some items of financial statements data, the number of companies in our sample is 140 companies in our sample.

2.1 Shariah-Compliance (Islamic Classification)

We obtain the data of Shariah (Islamic) stock classification from the Islamic scholar Dr. Al-Fozan for the period 2006 - 2015.g He is well known in Saudi Arabia as a Shariah scholar and an expert in Saudi stock market when it comes to classification. The Shariah classification reports are updated annually because some companies move from one category to another according to the aforementioned criteria. Thus, we update the sample to match Shariah classification reports. These reports are publicly available.

2.2 Variable Construction

We construct our main variable, negative skewness (NSKEW), by following Chen, Hong, and Stein (2001). NSKEW is calculated by taking the negative of the third moment of daily returns, and dividing it by the standard deviation of daily returns raised to the third power. Thus, for any stock i over any six-month period t; we have

$$\text{NCSKEW}_{it} = -\left(n(n-1)^{3/2}\sum R_{it}^{3}\right) \Big/ \left((n-1)(n-2)\left(\sum R_{it}^{2}\right)^{3/2}\right) \tag{1}$$

where R_{it} represents the sequence of de-meaned daily returns to stock *i* during period t; and n is the number of observations on daily returns during the period. The daily returns are calculated using log changes in a stock price.

By Following Chen, Hong, and Stein (2001), the second measure of crash risk is the down-to-up volatility measure (DUVOL) of the crash likelihood. For each stock i over a fiscal-year period t, firm-specific monthly returns are separated into two groups: 'down' months when the returns are below the annual mean, and 'up' months when the returns are above the annual mean, and we compute the standard deviation for each of these subsamples separately. DUVOL is the natural logarithm of the ratio of the standard deviation in the 'down' months to the standard deviation in the 'up' months:

$$\mathbf{DUVOL}_{it} = \log\left\{(n_{\mathrm{u}} - 1)\sum_{\mathrm{DOWN}} R_{it}^2 \Big/ \left((n_{\mathrm{d}} - 1)\sum_{\mathrm{UP}} R_{it}^2\right)\right\} \tag{2}$$

A higher value of DUVOL means a greater crash risk. Chen et al. (2001) suggested that DUVOL does not involve third moments and hence is less likely to be overly influenced extreme monthly returns.

$SIGMA_{it}$ is the standard deviation of stock *i* 's daily returns, measured over the six-month period t. Return is the cumulative return on stock *i*; also measured over the six-month period *t*. Size is the market capitalization calculated as the stock closing price at the end of the year times the number of shares outstanding. B/M is the lagged log of book to price ratio.

3 Empirical Work and Results

Table 32 show the correlation matrix of our main variables. The two crash risk measures, NSKEW and DUVOL are highly and significantly correlated.

They appear to be picking up much the same information although these two measures are totally different in their construction. NSKEW and DUVOL are negatively associated with MAX, which attracts the retail investor attention. Unlike MAX, the correlation between NSKEW and Islamic classification is weak while the correlation between Islamic classification and the other crash risk measure, DUVOL, is positive and significant.

3.1 Shariah Classification

We investigate whether Islamic classification forecast future crash risk in Saudi Stock Market. We use Al-Fozan reports for Islamic classification. He is well known in Saudi Arabia as a Shariah scholar and an expert in Saudi stock market when it comes to classification. Furthermore, many previous literatures use his classification (Alhomaidi, Hassan, Hippler, and Manum, 2019) to classify firms: Islamic and non-Islamic. We create an Islamic dummy variable that is equal to one if the firm is classified as Islamic or zero otherwise.

In Table 33, we do two-step Fama MacBeth (1973) regressions. We run a cross-sectional regression of NSKEWt+6 and NSKEWt+12 on subsets of one-month lagged predictor variables, including Islamic dummy variable. In the second step, we do the time-series averages of the monthly cross-sectional regression coefficients. The dependent variable of the first two columns is NSKEWt+6. In model 1, the coefficient on Islamic dummy variable is negative and statistically significant at 5% level. When we include the other control variables, the sign of the coefficient on Islamic dummy variable switches to positive and become insignificant. The same applies for NSKEWt+12. The relation between Islamic classification and negative skewness is not significant after including control variables.

For further investigation, we use the alterative measure of crash risk, DUVOL. We do two-step Fama MacBeth (1973) regressions. We run a cross-sectional regression of DUVOL on subsets of one-month lagged predictor variables, including Islamic dummy variable. In the second step, we do the time-series averages of the monthly cross-sectional regression coefficients. Unlike the result of NSKEW regressions, table 34 shows that the coefficient on Islamic dummy variable is positive and statistically significant at 10 % level or better. When we include the other control variables, the sign of the coefficient on Islamic dummy variable is still positive and statistically significant across all model specifications. The relation between Islamic classification and DUVOL is positive and significant even after including control variables.

3.2 MAX

We investigate whether the maximum daily return over the prior month (MAX) predict future crash risk in Saudi stock market. We create MAX by following Bali et al. (2011) use the maximum daily return in a month as a proxy for lottery-like features.

We follow Chen, Hong, and Stein (2001) approach in conducting this analysis. Table 35 presents our baseline cross-sectional regression specifications. We pool all the data and regress negative skewness

(NSKEWt+6 and NSKEWt+12) against on subsets of one-month lagged predictor variables, including MAX. In the univariate regressions (1) and (3), the coefficients on MAX are negative and statistically significant at 1% level. In model (2) and (4), we include one-months lagged negative skewness, sigma, log of market capitalizations of individual stocks, log of book-to-market and cumulative return on stock measured over the six-month. The coefficients on MAX are still negative and statistically significant at 1% level after including a set of control variables.

For further investigation, we do two-step Fama MacBeth (1973) regressions. In table 36, we run a cross-sectional regression of NSKEWt+6 and NSKEWt+12 on subsets of one-month lagged predictor variables, including MAX. In the second step, we do the time-series averages of the monthly cross-sectional regression coefficients. In the univariate regressions in model (1) and (3), the coefficients on MAX are negative and statistically significant at 10% level or better. When we include a set of control variables aforementioned, the coefficients on MAX are still negative and statistically significant at 1% level. For example, even when we use lead NSKEW 12-months ahead, the coefficient on MAX is -0.67 (t-statistics= -3.82). This indicates that MAX is negatively associated with future crash risk in Saudi Stock Market.

For robustness check, we use the alternative measure of crash risk, DUVOL. We run two-step Fama MacBeth (1973) regressions. In table 37, we run a cross-sectional regression of DUVOL on subsets of one-month lagged predictor variables, including MAX. In the second step, we do the time-series averages of the monthly cross-sectional regression coefficients. In the univariate regressions in model (1), the coefficients on MAX are negative and statistically significant at 1% level, and this is even stronger than the results of NSKEW regression. When we include a set of control variables aforementioned, the coefficients on MAX are still negative and statistically significant at 10% level or better. This is a clear evidence that MAX is negatively associated with future crash risk in Saudi Stock Market.

4 Discussion

Shariah classification and MAX are important effects in Saudi Stocks Market. It is interesting to examine whether stocks with those characteristics (Islamic or lottery-features) are more prone to price crash. Our analysis shows the relation between Shariah classification and future stock price crash risk is not robust. In contrast, we find evidence that MAX is significantly and negatively associated with future stock price crash risk. One possible explanation is Wen et al. (2019) who show that firms with higher retail investor attention tend to have a lower future stock price crash risk. When a firm attracts individual investor's attention, the investor might seek more information about the firm (Gao, Wang, Wang, and Liu, 2018), which in turns mitigates the information asymmetry problem (Ding and Hou, 2015). In this research, we are not testing the explanation of Wen et al. (2019). We just suggest it as a possible explanation, and we leave this phenomenon to be investigated in future research.

MAX and Islamic classification have similar effects on retail investor attention, but also they have different results when it comes to forecasting future crash risk. This makes our paper different from Wen et al. (2019) because we show two different variables, which both attract retail investors, have different results for future crash risks. We leave this for future research.

5 Conclusion

We examine whether Islamic classification and MAX lottery-like stocks exhibit a higher future crash risk in Saudi Stock Market, where 90 percent of its stocks are traded by local retail investors. We find that MAX is negatively associated with future crash risk after controlling for other predictors of crash risk. However, the association is not clear between Islamic classification and future stock price crash risk.

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Table 31: Descriptive Statistics of Main Variables

Variable	Mean	SD	Min	p5	p25	p50	p75	p95	Max
NSKEW	-0.02	1.11	-9.82	-1.48	-0.43	0.02	0.48	1.33	13.34
DUVOL	-0.12	0.67	-4.32	-1.19	-0.53	-0.11	0.27	0.94	4.50
SIGMA	2.15	0.85	0	1.05	1.54	2.01	2.63	3.64	9.37

Note: This table reports summary statistics of variables: NCSKEW and SIGMA. Negative skewness (NSKEW) is −1 times skewness of (daily) returns measured over a given six-month period. DUVOL is "down-to-up volatility", the log of the ratio of the standard deviation in the 'down' months to the standard deviation in the 'up' months. Sigma is the (daily) standard deviation of returns measured over a given six-month period. The sample period is 2006-2018

Table 32: Descriptive Statistics: Correlation matrix

	NSKEW	DUVOL	MAX	ISLAMIC	SIGMA	SIZE	M/B
NSKEW	1.00	0.19	-0.07	0.00	0.09	-0.06	-0.09
DUVOL		1.00	-0.03	0.04	-0.05	0.02	-0.07
MAX			1.00	-0.07	0.39	-0.16	0.12
ISLAMIC				1.00	-0.11	-0.08	0.03
SIGMA					1.00	-0.39	0.15
SIZE						1.00	-0.02
M/B							1.00

This table presents the correlation matrix of the main research variables. NSKEW is the negative coefficient of (daily) skewness measured over a given six-month period, and it is t+12. DUVOL is "down-to-up volatility", the log of the ratio of the standard deviation in the ‘down’ months to the standard deviation in the ‘up’ months. Max is the maximum daily return over the past one month. Sigma is the (daily) standard deviation of returns measured over a given six-month period. Islamic is dummy variable , equal to one if the firm is classified as Islamic or zero otherwise. Size is the lagged log of market chaptalization of the individual stocks calculated by multiplying the share price by the number of shares outstanding. M/B is the lagged log of price to book ratio.

Table 33: FMB Regressions – Forecasting Crash Risk: Islamic Classification

	Dependent Variable			
	$NSKEW_{t+6}$		$NSKEW_{t+12}$	
Independent Variable	(1)	(2)	(3)	(4)
Islamic Dummy	-1.27	0.64	-1.46	0.87
	(-2.07)	(1.11)	(-2.20)	(1.37)
NSKEWt		0.46		0.14
		(10.19)		(6.30)
Sigma		0.17		0.30
		(4.84)		(9.45)
Size		0.22		0.71
		(0.71)		(2.24)
B/M		4.31		6.93
		(9.55)		(14.80)
Return		0.01		0.02
		(0.01)		(1.89)
R-squared	0.01	0.33	0.02	0.16

Notes: This table reports Fama–MacBeth regressions of negative skewness on subsets of one-month lagged predictor variables. The dependent variables are $NSKEW_{t+6}$ and $NSKEW_{t+12}$, the negative coefficient of (daily) skewness measured over a given six-month period and t+6 is 6 months ahead and the same applies for t+12. Islamic dummy variable is equal to one if the firm is classified as Islamic or zero otherwise. Sigma is the (daily) standard deviation of returns measured over a given six-month period. Size is the lagged log of market chaptalization of the individual stocks calculated by multiplying the share price by the number of shares outstanding. B/M is the lagged log of book to price ratio. Return is the cumulative return on stock measured over the six-month period. Numbers shown in the parentheses are t-statistics.

Table 34: FMB Regressions – Forecasting Crash Risk: Islamic Classification

	Dependent Variable = DUVOL			
Independent Variable	(1)	(2)	(3)	(4)
Islamic Dummy	0.03	0.22	0.04	0.05
	(2.24)	(1.77)	(3.79)	(5.46)
Sigma		-0.01	-0.00	-0.01
		(-3.94)	(-3.56)	(-0.67)
Size			0.01	0.02
			(1.06)	(2.07)
B/M				0.10
				(6.59)
Return				-0.01
				(-1.94)
R-squared	0.01	0.03	0.06	0.11

Notes: This table reports Fama–MacBeth regressions of DUVOL on subsets of one-month lagged predictor variables. The dependent variable is DUVOL, "down-to-up volatility", the log of the ratio of the standard deviation in the ‘down’ months to the standard deviation in the ‘up’ months. Islamic dummy variable is equal to one if the firm is classified as Islamic or zero otherwise. Sigma is the (daily) standard deviation of returns measured over a given six-month period. Size is the lagged log of market chaptalization of the individual stocks calculated by multiplying the share price by the number of shares outstanding. B/M is the lagged log of book to price ratio. Return is the cumulative return on stock measured over the six-month period. Numbers shown in the parentheses are t-statistics.

Table 35: Forecasting Skewness in the Cross-Section: Pooled Regressions

	Dependent Variable			
	$NSKEW_{t+6}$		$NSKEW_{t+12}$	
Independent Variable	(1)	(2)	(3)	(4)
MAX	-0.52	-0.42	-0.49	-0.95
	(-7.10)	(-5.59)	(-6.28)	(-11.01)
$NSKEW_t$		0.39		0.09
		(40.24)		(8.78)
Sigma		0.07		0.22
		(5.73)		(14.56)
Size		-0.34		-0.44
		(-2.30)		(-2.64)
B/M		2.61		4.44
		(7.63)		(11.46)
Return		0.01		0.07
		(1.13)		(8.32)
R-squared	0.01	0.16	0.001	0.04

Notes: This table reports pooled regressions of negative skewness on subsets of one-month lagged predictor variables. The dependent variables are $NSKEW_{t+6}$ and $NSKEW_{t+12}$, the negative coefficient of (daily) skewness measured over a given six-month period and t+6 is 6 months ahead and the same applies for t+12. Max is the maximum daily return over the past one month. Sigma is the (daily) standard deviation of returns measured over a given six-month period. Size is the lagged log of market chaptalization of the individual stocks calculated by multiplying the share price by the number of shares outstanding. B/M is the lagged log of book to price ratio. Return is the cumulative return on stock measured over the six-month period. Numbers shown in the parentheses are t-statistics.

Table 36: FMB Regressions – Forecasting Skewness: MAX

	Dependent Variable			
	$NSKEW_{t+6}$		$NSKEW_{t+12}$	
Independent Variable	(1)	(2)	(3)	(4)
MAX	-0.49	-0.61	-0.31	-0.67
	(-3.00)	(-4.03)	(-1.69)	(-3.82)
NSKEWt		0.42		0.13
		(11.06)		(7.42)
Sigma		0.21		0.34
		(6.91)		(10.48)
Size		0.02		0.36
		(0.09)		(1.32)
B/M		3.60		5.95
		(8.93)		(13.27)
Return		0.01		0.02
		(0.56)		(2.10)
R-squared	0.03	0.32	0.02	0.16

Notes: This table reports Fama–MacBeth regressions of negative skewness on subsets of one-month lagged predictor variables. The dependent variables are $NSKEW_{t+6}$ and $NSKEW_{t+12}$, the negative coefficient of (daily) skewness measured over a given six-month period and t+6 is 6 months ahead and the same applies for t+12. Max is the maximum daily return over the past one month. Sigma is the (daily) standard deviation of returns measured over a given six-month period. Size is the lagged log of market chaptalization of the individual stocks calculated by multiplying the share price by the number of shares outstanding. B/M is the lagged log of book to price ratio. Return is the cumulative return on stock measured over the six-month period. Numbers shown in the parentheses are t-statistics.

Table 37: FMB Regressions – Forecasting Crash Risk: MAX

	Dependent Variable = DUVOL			
Independent Variable	(1)	(2)	(3)	(4)
MAX	-0.02	-0.01	-0.01	-0.01
	(-3.65)	(-2.84)	(-2.91)	(-1.74)
Sigma		-0.01	-0.00	0.00
		(-1.36)	(-1.76)	(0.24)
Size			-0.01	0.01
			(-0.21)	(1.00)
B/M				0.09
				(7.02)
Return				-0.01
				(-3.01)
R-squared	0.02	0.04	0.07	0.12

Notes: This table reports Fama–MacBeth regressions of DUVOL on subsets of one-month lagged predictor variables. The dependent variable is DUVOL, "down-to-up volatility", the log of the ratio of the standard deviation in the 'down' months to the standard deviation in the 'up' months. Max is the maximum daily return over the past one month. Sigma is the (daily) standard deviation of returns measured over a given six-month period. Size is the lagged log of market chaptalization of the individual stocks calculated by multiplying the share price by the number of shares outstanding. B/M is the lagged log of book to price ratio. Return is the cumulative return on stock measured over the six-month period. Numbers shown in the parentheses are t-statistics.